Universidade do Porto
Faculdade de Engenharia
FEUP

Transmission Expansion Planning - A Dynamic Multiobjective Approach Considering Uncertainties

Phillipe Vilaça Gomes

Thesis submitted to the Faculty of Engineering of University of Porto
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

Thesis Supervisor: João Paulo Tomé Saraiva
Professor at the Department of Electrical and Computer Engineering
Faculty of Engineering, University of Porto

October 23, 2018

This work was supported by the Coordination for the Improvement of Higher Education Personnel (CAPES, Brazil) under Grant 13207-13-0, by the Portuguese Foundation for Science and Technology (FCT) and by the Centre for Power and Energy Systems of the Institute for Systems and Computer Engineering, Technology and Science – INESC TEC, Portugal.

...Look again at that dot. That's here. That's home. That's us. On it everyone you love, everyone you know, everyone you ever heard of, every human being who ever was, lived out their lives. The aggregate of our joy and suffering, thousands of confident religions, ideologies, and economic doctrines, every hunter and forager, every hero and coward, every creator and destroyer of civilization, every king and peasant, every young couple in love, every mother and father, hopeful child, inventor and explorer, every teacher of morals, every corrupt politician, every "superstar," every "supreme leader," every saint and sinner in the history of our species lived there-on a mote of dust suspended in a sunbeam. The Earth is a very small stage in a vast cosmic arena. Think of the endless cruelties visited by the inhabitants of one corner of this pixel on the scarcely distinguishable inhabitants of some other corner, how frequent their misunderstandings, how eager they are to kill one another, how fervent their hatreds. Think of the rivers of blood spilled by all those generals and emperors so that, in glory and triumph, they could become the momentary masters of a fraction of a dot...

The pale blue dot - Carl Sagan

To Isabella and Manuella, with love.

Acknowledgements

First of all, I would like to thank Professor João Tomé Saraiva for all the help and support in the last four years. All the discussions on the subject of this thesis, the active participation in the published papers, his dedication as a supervisor and commitment with high quality standards were fundamental for this work. Moreover, his simple and sincere way of dealing with people inspires me to be a better person and professional.

I would like to thank the Professors from the Faculty of Engineering of the University of Porto who also contributed in the improvement of my background, especially Professors Vladimiro Miranda, Nuno Fidalgo, João Abel Peças Lopes and José Fernando Oliveira. I should also provide further thanks to some Professors from the Faculty of Engineering of the Federal University of Juiz de Fora who had patience and passion in teaching, and inspired me a lot on my professional path, particularly the Professors Augusto Santiago Cerqueira, Ivo Chaves Junior, Bruno Dias, Pedro Gomes, Edimar Oliveira and Leonardo Willer.

An acknowledgment is also due to the people of INESC TEC. Working with this team was the best opportunity I had to improve my research for this thesis. The friendship and daily lightness was of extreme importance in this journey. A special thanks to the co-authors Leonel Carvalho, Jean sumaili, Mario Coelho, Nelson Knack and João Silva who made valuable contributions in the papers published for this thesis.

I would also like to thank the great friends I made here in Portugal, friendships that I will take for the rest of my life. To my great friends who have supported me for the last fifteen years and that are very important to me, Diogo Dadalti, Fernanda Botega, Diego Moreira, Artur Miranda and Daniel Esteves, I can never pay them back enough for what they did for me.

Many thanks to all my family, especially Wilson Francisco Ferreira, Martha Cristina Vilaca, Allan Vilaca, Carla Vilaca, Imaculada Liquer, Vó Eulza, Vô Tatão, Felipe Liquer, Priscila Nader and Leticia Gonelli. Thank you for being so important in my life.

Last but not least, this thesis is dedicated to Isabella Ribeiro Liquer, my beloved wife and mother of my child, Manuella - my greatest gift. Thank you for having supported me so much for the last twelve years and to have been my faithful companion on this journey, this thesis would never be possible without your affection and motivation.

Abstract

Transmission Expansion Planning (TEP) has the purpose of identifying new equipments to be inserted on a transmission grid to optimize some pre-defined objective function while ensuring the secure and economic supply of the demand forecasted along an extended planning horizon. Its non-linear and non-convex natures turn TEP a challenging problem. In addition, the phenomenon of combinatorial explosion of investment alternatives typically requires a huge computational effort to solve it.

In recent years TEP has been approached with relaxed mathematical models to overcome these challenges, even though there is no guarantee that the optimal solution of the relaxed problem is even feasible if tested in the original real problem. Moreover, in the last years, power systems have been changing towards a more active load pattern, where consumers also produce electricity and now act as ”prosumers”, mainly due to advances related with the dissemination of Distributed Energy Resources (DERs) as Distributed Generation (DG), electric vehicles, energy storage, smart grids, microgrids and demand response programs. To further increase the challenges of TEP problems, the share of renewable energy sources with intermittent, reduced predictability and controllability characteristics is increasing, and the mathematical models should take this issue into account. Besides, the unbundling of the electricity sector in several activities, some of them provided in a regulated way and some others under competition, poses a number of challenging problems namely because in several areas there are conflicting objectives associated to different stakeholders.

In order to overcome these issues, this Thesis compares different mathematical models regarding the accuracy and time required to solve the TEP problem. Besides, new algorithms and techniques are proposed in order to improve the computational performance in solving the problem. In this Thesis it is also evaluated the impact under several scenarios of solar DGs and electric vehicle charging policies in the planning task. The uncertainties in renewable energy, electric demand and equipment availability are also addressed as well as the impact of the most common decision-making processes adopted in the TEP literature and on the total system cost. A new worst-case parameter is proposed in order to ensure that the system is sufficiently robust to overcome conditions with high electricity demand and low renewable energy generation. Finally, a novel efficient method is proposed to handle with the proposed multiobjective optimization TEP formulation required to give a trade-off between the specified objectives.

The results indicate that although relaxed mathematical models can solve the TEP problem faster, they may display unreliable and in some cases even unfeasible solution plans. Besides, other techniques as reduction of the search space and parallel computing can be

allied to real mathematical models in order to get reliable solutions in a timely manner. The results also indicate that distributed generation can enable the reduction of operation costs, transmission losses and emissions, although it is only possible to reduce investment costs in new equipment if the peak load is also reduced by the DGs. Regarding the impact of electric vehicles, the investments in new equipment could be postponed if it is adopted an efficient management approach to control the charging that includes the “valley-filling effect” and/or the “peak-shaving effect”. Besides, numerical simulations proved that the TEP conducted considering only the peak load to quantify investment requirements is not sufficient to ensure the safe operation of the system in normal conditions for any other off-peak load scenarios. Finally, the results obtained allow concluding that multiobjective approach gives the decision maker a higher flexibility to decide as well as more information about the solutions presented, which in turn are associated to trade-offs between the specified objectives.

Resumo

O Planeamento da Expansão da Rede de Transmissão (Transmission Expansion Planning, TEP, em língua Inglesa) tem como objetivo identificar novos equipamentos a serem inseridos numa rede de transmissão de energia elétrica para otimizar uma função objetivo pré-definida alimentando de forma segura e económica a carga prevista ao longo de um horizonte temporal mais ou menos alongado. Este problema tem natureza não linear e não convexa o que o converte num problema desafiador. Por outro lado, a explosão combinatória de alternativas de planeamento requer em geral um enorme esforço computacional.

Nos últimos anos, o TEP tem sido abordado com modelos matemáticos relaxados para superar estes desafios, embora não haja garantia de que as soluções ótimas do problema relaxado sejam sequer factíveis se avaliadas no problema real original. Por outro lado, nos últimos anos, os sistemas de energia têm sofrido alterações profundas para um padrão de carga mais ativo, em que existe capacidade de produção nas instalações dos consumidores finais tornando-os *prosumers*, principalmente devido aos avanços relacionados com os Recursos Energéticos Distribuídos (DERs), como a geração distribuída, os veículos elétricos, o armazenamento de energia, as redes inteligentes, as micro redes e os programas de *demand response*. Para aumentar ainda mais os desafios associados ao TEP, as fontes de energia afetadas por intermitência, reduzida previsibilidade e controlabilidade dos recursos primários têm aumentado cada vez mais a sua participação no mix energético, pelo que os modelos matemáticos devem considerar esta questão. Além disso, a desverticalização do setor elétrico em diversas atividades, algumas das quais providas de forma regulada e outras sob competição, coloca novos desafios, principalmente porque em várias áreas existem objetivos conflituantes, associados a diferentes agentes.

Para superar estes problemas, esta Tese compara diferentes modelos matemáticos em relação à precisão e tempo necessário para resolver o problema TEP. Além disso, são propostos novos algoritmos e técnicas para melhorar o desempenho computacional na solução do problema. Nesta Tese também é verificado o impacto sob vários cenários de geração distribuída de tipo PV bem como diferentes estratégias de carregamento de veículos elétricos na tarefa de planeamento. As incertezas associadas às fontes de energia renovável, demanda elétrica e disponibilidade de equipamentos também são abordadas, bem como o impacto dos processos de tomada de decisão mais comuns adotados na literatura da TEP e seu impacto no custo total do sistema. Um novo parâmetro de pior caso é proposto para garantir que o sistema seja suficientemente robusto para superar as condições associadas a elevada demanda de eletricidade e baixos níveis de produção a partir de fontes de energia renovável. Por fim, um novo método eficiente é proposto

para lidar com a formulação multiobjetivo desenvolvida para a o TEP de modo a fornecer *trade-offs* entre os objetivos considerados.

Os resultados obtidos indicam que, embora os modelos matemáticos relaxados possam resolver o problema do TEP mais rapidamente, eles podem permitir obter planos de expansão não confiáveis. Além disso, outras técnicas como redução do espaço de busca e a computação paralela podem ser aliadas a modelos matemáticos mais realistas para obter soluções confiáveis em tempo útil. Os resultados obtidos também indicam que a geração distribuída pode proporcionar redução dos custos de operação, das perdas nas linhas de transmissão e das emissões, embora só seja possível reduzir os custos de investimento em novos equipamentos se a ponta de carga também também for diminuída. Em relação ao impacto dos veículos elétricos, os investimentos em novos equipamentos poderão ser postergados se for adotada uma abordagem de gestão eficiente para controlar o carregamentoque inclui o *valley-filling effect* e/ou o *peak-shaving effect*. Além disso, as simulações numéricas realizadas comprovaram que o TEP conduzido considerando apenas a ponta de carga para quantificar os requisitos de investimento não é suficiente para garantir a operação segura do sistema em condições normais para quaisquer outros cenários de carga fora desse período. Por fim, os resultados obtidos permitem concluir que a formulação multiobjetivo fornece ao agente de decisão uma maior flexibilidade na tomada de decisões, bem como mais informações sobre as soluções apresentadas, bem como o trade-off entre os objetivos considerados.

Contents

Nomenclature

$*$	Index for muted parameter
α	Load reduction flexibility (AC-OPF)
β_1	Penalization factor for PNS
β_2	Penalization factor for N-1
β_V	Coefficient of variation (MCS)
β_V^{stop}	Stop criterion (MCS)
χ	Position of a particle
Δt	Duration of a load block
δ	Equipment investment state
κ	Present-worth value coefficient
λ	Equipment failure rate
μ_s	Average value for the solar irradiation
μG	Microgrids
μ	Equipment repair rate
μ_u	Average value for the wind
ν	Velocity of the particles
Ω^{ce}	Set of candidate equipment
Ω_i	Set of all buses directly connected to bus i
Φ	Set of all system instability states
π	Lagrange multiplier of the real power balance equation
Ψ	EPSO communication factor
ψ_1	Direct cost coefficient
ψ_2	Underestimation cost coefficient
ρ	Variable representing probability
σ_s	Standard deviation for the solar irradiation
σ_u	Standard deviation for the wind

τ	Gamma function
Θ	Voltage angle
Υ	Set of all system states with power not supplied
ε	Cost coefficient of thermal units
A	Argument of the portfolio of indices CHA
$ADLC$	Average Duration of Load Curtailments
B	Branch susceptance matrix
b_{ij}	Susceptance in branch i-j
B_{pdf}	Beta PDF
bus	Index for buses
b_{ij}^{sh}	Shunt susceptance of the transmission line i-j
$C(P_G)$	Operation cost function
c_1	Weighting function - inertia
c_2	Weighting coefficients - individual knowledge
c_3	Weighting coefficients - collective knowledge
C_{eq}	Cost of equipment eq
C_{inv}	Investment cost
C_{op}	Operation cost
C_{tot}	Total cost of the system
C_{ue}	Unserved energy cost
Cap	Capital cost
CDF	Customer Damage Function
CHA	Constructive Heuristic Algorithm
d	Discount rate
D_i	Duration of state i
$DERs$	Distributed Energy Resources
DG	Distributed Generation
$DisCo$	Distribution companies
DR	Demand Response
$EDLC$	Expected Duration of Load Curtailments
$EDNS$	Expected Demand Not Supplied
$EENS$	Expected Energy not Supplied
$EFLC$	Expected Frequency of Load Curtailments

$EPSO$	Evolutionary Particle Swarm Optimization
eq	Index for candidate equipment
f_{ij}^{max}	Maximum active power flow allowed in the branch connecting bus i to j
f_c	Scale factor (W_{pdf})
$F_s(x)$	Function to evaluate the adequacy of the state x
f_{af}	Average failure frequency
F_{ger}	Power generation cost function
f_{sh1}	Shape parameter (B_{pdf})
f_{sh2}	Scale factor (B_{pdf})
f_{sh}	Shape factor (W_{pdf})
$FACTS$	Flexible Alternating Current Transmission System
FF	Fill factor
Fls_i	Frequency to move for a state i with PNS
FOR	Forced Outage Rate
ft_i	Frequency of transition from a state with PNS to other system state i also with PNS
G	Branch conductance matrix
g_{best}	Best solution found by the swarm
g_{ij}	Conductance in branch i-j
GA	Genetic Algorithm
$GenCo$	Generation Company
GEP	Generation Expansion Planning
ger	Index for power generator
$HVDC$	High-voltage Direct Current
I_g	Current characteristic of a PV module
I_{sc}	Short circuit current
$IMPP$	Current at maximum power point
ISO	Independent System Operator
it	Index for iteration
k	Argument of the sigmoid CHA
k_c	Current temperature coefficient
k_v	Voltage temperature coefficient
lb	Index for load blocks

$LOLC$	Loss of Load Costs
$LOLE$	Loss of Load Expectation
$LOSS_{ij}$	Branch losses between busses i and j
MCS	Monte Carlo Simulation
$MTTF$	Mean time to failure
$MTTR$	Mean time to repair
N	Diagonal matrix containing vector n_{ij}
$N-1$	Single Contingency Criterion
N^0	Diagonal matrix containing vector n_{ij}^0
N_x	Number of states in a sample of X
N_{cont}	Number of single contingencies associated to network equipments that are not meeting the N-1 condition
n_{ij}	Number of circuits to be built from i to j
N_{mod}	Number of PV modules
N_{proj}	Number of candidate equipments
n_{udr}	Uniformly random number
$nbus$	Number of buses in the system
neq	Number of candidate equipment
$nger$	Number of power generators
nlb	Number of load blocks
Not	Nominal operating temperature
np	Number of periods
nsa	Number of outage scenarios
nsc	Number of scenarios of net peak
$nsol$	Number of solar plants
$nter$	Number of thermal units
nwd	Number of wind farms
${n_{ij}}^0$	Number of circuits in base topology from i to j
OF	Objective Function
OPF	Optimal Power Flow
p	Index for periods
$P(V,\Theta,n)_{bus}$	Real power injected on the bus
P^{av}	Available renewable power

P_D	Real power demand
P_G	Real power generation
p_{best}	Best solution found by a particle
$P_{G_{max}}$	Maximum allowed real power
$P_{G_{min}}$	Minimum allowed real power
PE	Expansion parameter - Sigmoid CHA
Per	Rated wind power
$PEVs$	Plug-in Electric Vehicles
PLC	Probability of Load Curtailments
PNS	Power Not Supplied
PSO	Particle Swarm Optimization
Psp	Output power of a solar plant
PV	Photovoltaic
Pwt	Output power of a wind turbine
$Q(V,\Theta,n)_{bus}$	Reactive power injected on the bus
Q_D	Reactive power demand
Q_G	Reactive power generation
$Q_{G_{max}}$	Maximum allowed reactive power
$Q_{G_{min}}$	Minimum allowed reactive power
r	EPSO replication parameter
$rand$	Random number in [0,1]
RES	Renewable Energy Sources
S	Transposed incidence node-branch matrix
s	Solar irradiance
$S^{to,from}$	Apparent power flow vectors in the branches in both terminals
sa	Index for outage scenarios
SI	Sensitivity indicator of a CHA
sol	Index for solar plants
SSS	Size of the search space
T	Time length (hours)
T^{com}	Commissioning year
t_f	Time to fail
t_r	Time to repair

t_x	Shortest time (chronological MCS)
T_{cg}	Cell temperature
TA	Ambient temperature
TEP	Transmission Expansion Planning
ter	Index for thermal units
$TransCo$	Transmission companies
u	Wind speed
u_c	Cut-in wind speed
u_f	Cut-out wind speed
u_r	Rated wind speed
V	Voltage magnitude
V_g	Voltage characteristic of a PV module
V_{oc}	Open circuit voltage
$VMPP$	Voltage at maximum power point
W	Customer damage function
w_{i1}	Weight conditioning the inertia term in particle i
w_{i2}	Weight conditioning the memory of each particle i
w_{i3}	Weight conditioning the cooperation inside the swarm for each particle i
w_{i4}	Term used to mutate g_{best}
W_{pdf}	Weibull PDF
wd	Index for wind farm
X	Set of all possible system states
x_{ij}	Reactance in branch i-j
$Y = G + jB$	Branch admittance matrix

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Chapter 1

Introduction

1.1 The evolution of the electric sector and planning

The activities of generation, transmission and distribution of electricity began in the late XIX century in order to supply modest load centers by small power networks with limited geographic extension. As the electricity demand and the consumer centers increased, together with the availability of technological innovations, the electric networks also started to be expanded. This process was developed in a scenario in which the electricity generation was generally far away from the load centers and, therefore, transmission networks have been increasingly expanded. Thus, the power system evolved into a robust system, which was increasingly requiring more financial resources and large geographic extensions.

After World War II, several countries experienced a nationalization process in the electricity sector with the intention of, among others, completing the electrification effort of large geographical areas. This process was also accompanied by the vertical integration of the electricity sector although there were differences between public models like what happened in Portugal, France and Brazil and private ones, such as Germany and Spain. However, in any of these cases it is possible to identify two very clear characteristics of the electric sector during that period (Saraiva et al., 2002):

i Generation Companies (GenCos) were dedicated not only to electricity production but also to transmission, distribution and the relationship with the end customer, in what it is usually termed as Vertical Companies;

ii Although, in some cases, there were several companies operating in a country, these companies had defined concession areas, so there was not any competition and each consumer was tied commercially and physically to the same entity.

This vertically integrated structure is shown in Fig. 1.1 in which a power company has a dominant position in all areas of the electricity sector. This framework had some striking features, such as the impossibility of consumers to choose the supplier with which it wished to establish commercial relationships. Therefore, the main disadvantage of the vertical model is the lack of competition along the electrical system and therefore, it is typically associated to a reduced level of incentives for efficiency and innovation. Besides, the electricity prices were governed by simple tariff regulation procedures (mainly cost of service and rate of return) that basically remunerated the company according to its assets and incurred costs. However, an adequate remuneration might not be guaranteed due the asymmetry of information intrinsically associated to this kind of regulation (Calabria, 2016). In addition, the vertically structured power system typically had a strong impact on the economy and, therefore, the tariffs often were subjected to some political arrangements, namely in periods of economic crisis.

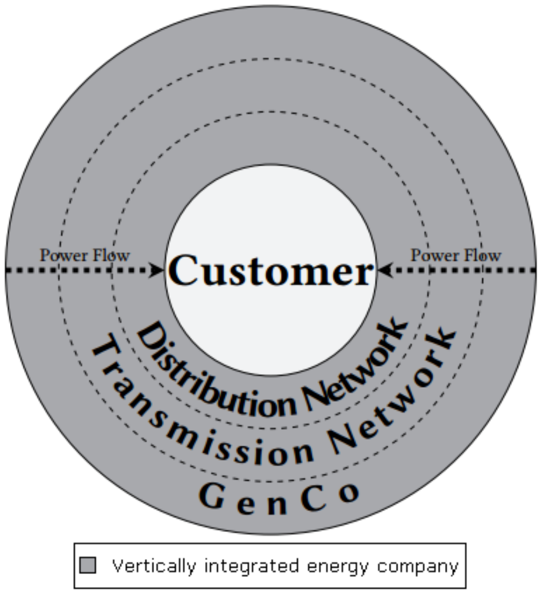

Figure 1.1: Vertical integrated structure of the electric sector.

In 1973, after the oil crisis, the economic environment became more unstable and several activities, as well as the electricity sector, were very affected. Moreover, after the 80s several economic activities began to be deregulated or liberalized so that more agents started to act and a more intensified competition was introduced. As a result, customers started to gain a more active role. All these factors contributed to the creation of an atmosphere of change namely in the electricity sector. Additionally, the process of restructuring of this sector was intensified or induced by the following factors:

i New regulations and regulatory policies were adopted in several countries in order to implement market mechanisms (mainly encouraging competition in some sector segments), which resulted in the separation of vertically integrated companies in several areas of activity;

ii The implementation of these new market mechanisms required the simultaneous use of networks by different generation agents, large consumers or retailers, and consequently, new strategies for automation, supervision and control of these networks were progressively introduced. Thus, the technological developments in telecommunications and computing that occurred in the 80s and 90s were essential to enable this transformation;

iii The provision of services of prime necessity carried out by the electricity sector proved to be economically attractive so that more investors were interested in operating in this sector.

Thus, the first modification of the electricity sector in this direction occurred in Chile in 1980 followed by England and Wales in 1990 and then followed by many other countries such as Argentina in 1992, Australia in 1994, New Zealand in 1996, etc. In addition to the atmosphere of change, the restructuring of the electricity sector also originated the creation of new business structures (generation, transmission, distribution and retailing of electricity) as well as, new independent agencies designed to regulate or coordinate the industry. Thus, the generation activity of each vertical energy company gave rise to one or more new companies operating in this area. The number of new companies depended on the original size of the sector segment and the need to create a competitive environment. Typically, the transmission activity was assigned to only one company operating as a natural monopoly, since it is neither practical nor cost effective to have competition between grid companies namely because duplicating power lines would be extremely inefficient or impossible for technical and environmental reasons. Distribution networks originate new distribution companies decoupling this network activity from the commercial relationship of these companies with their customers. Therefore, this commercial relationship gave rise to a new sector called retailing also under competition while the distribution network companies were under regional natural monopolies. Fig. 1.2 illustrates the vertical segmentation of the sector as well as the horizontal decoupling of the generation and retailing activities in several competing entities.

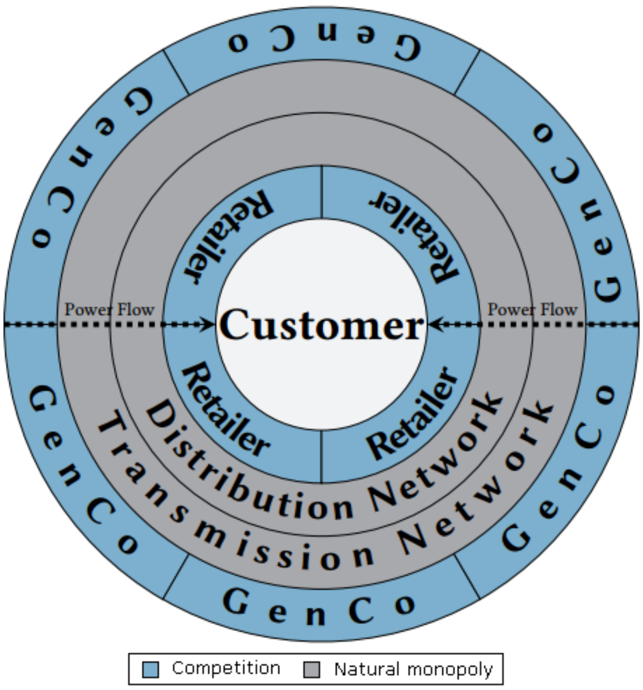

Figure 1.2: Unbundling of the traditional vertical companies.

In this new unbundled structure, the transmission network activity was not exclusively related to the construction and maintenance of its equipments (transmission lines, cables and transformers), but also related to the expansion planning task. In addition, with the unveiling of energy companies, new activities were created in a disaggregated structure.

Related with the transmission sector and the need to coordinate the operation of the whole system, the following activities can be associated to what was originally assigned to control centers and the transmission segment (Saraiva et al., 2002):

i **Bilateral contracts** – Contracts between the generators and retailers or eligible/large customers in a direct way in which prices, electricity demand and generation are set for a period of time;

ii **Centralized electricity markets** – Mechanisms that obtain an economic schedule based on the clearing of the buying and selling electricity bids;

iii **Independent System Operator (ISO)** – Entity that is charge of the technical feasibility studies regarding the set of pre-established contracts and economic schedules. It also has the function of technical coordination of the transmission sector and its real time supervision and operation;

iv **Ancillary services** – Entities that provide reserve services, reactive power/voltage control, frequency regulation, etc. In the past, the provision of these services was embedded in the vertical companies but under a restructured model some of them can be procured and contracted in specific markets managed by the ISO.

A direct implication of the power sector reform was the huge increase in the complexity of the Transmission Expansion Planning (TEP) tasks. As generation activities became driven by competition, investors became free to choose where and when to build new power plants, although most of the times subjected to an authorization procedure or to some sort of auction processes. However, transmission planners need to know which/when/where generators will be built to identify which equipments should reinforce/expand the transmission system and to allocate transmission costs over the network users. On the other hand, generation investors also need to know the transmission tariffs to decide where to build new generation facilities. This situation is known as ”the chicken or the egg” dilemma (Barroso et al., 2007) and is usually overcome by coordinating studies of Generation Expansion Planning (GEP) with TEP (Alayo et al., 2017).

The integration of Renewable Energy Sources (RES) as wind and solar into power systems also increases the complexity of the TEP tasks. In fact, the intermittent nature combined to the low predictability and controllability of RES represent additional challenges to grid planers and operators to maintain acceptable levels of reliability and security of supply. Besides, the mathematical models must incorporate the impact of wind farms and solar plants in future operating costs once their intermittent nature may influence the amount of reserves to be procured and contracted. To further increase the complexity of the TEP problem, a significant amount of RES are being connected closer to the load centers or even in the distribution system, contributing to modify the traditional generation-transmission-load patterns to be considered in TEP studies.

Moreover, in the last years, power systems have been changing towards a more active load pattern, where consumers also produce electricity and now acting as ”prosumers”, mainly due to advancements related with the Distributed Energy Resources (DERs) as distributed generation, electric vehicles, energy storage, smart grids, microgrids and demand response. In fact, as the number of these elements grows, they will affect the behavior of the electricity demand seen not only by distribution but also by transmission networks and these changes will certainly impact on the operation and expansion planning of the power systems.

DERs technologies have the potential to provide new services, namely on the distribution networks, so that many industry stakeholders claim that DER aggregators create economic value by enabling these services (Burger et al., 2016). Even though there are still several discussions about how these aggregators should work (mainly about the interface with the retail markets). Additionally, the new electrical system's paradigm, with more and more distributed elements, indicates a new evolution step for power systems where power flows do not run only according to the traditional generation-transmission-distribution-load direction but also to the opposite side. Therefore, both energy and information flows are becoming bidirectional so that the prosumer can send information to the providers about service provision, billing and problem resolution (Valocchi et al., 2014).

Obviously, the mathematical formulation of the TEP problem should take into account all these new modifications and evolutions of the power sector, which will certainly increase in the near future thus requiring additional computational efforts to solve the TEP problem. This new and to some extent already existing paradigm is illustrated in Fig. 1.3.

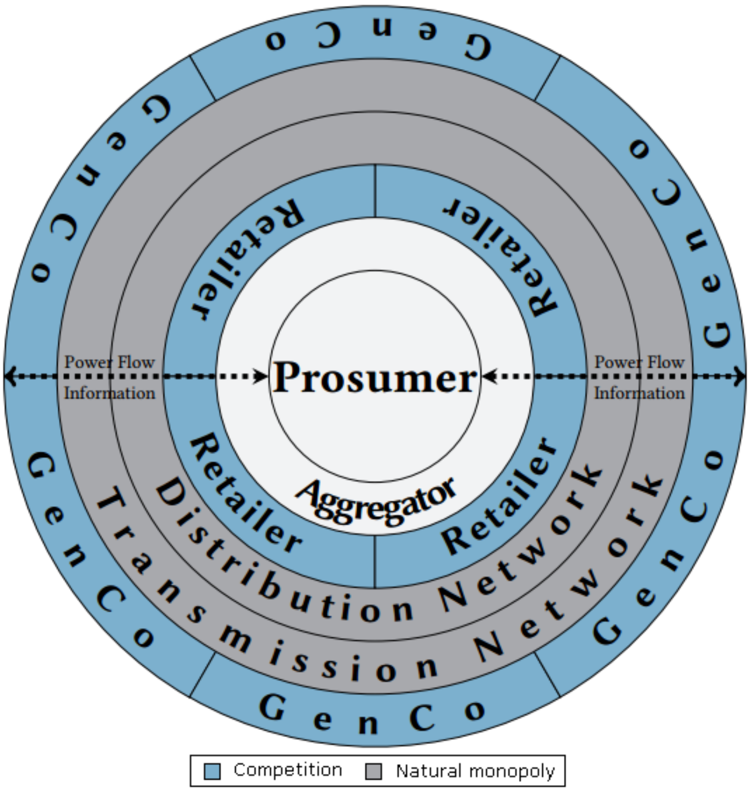

Figure 1.3: The electricity sector under a new business model.

1.2 Thesis motivations and research questions

The economic development increases the demand for electricity, and thus, it requires a thorough planning in such a way that the power system can meet the future load in an economic and reliable way. The changes on the power system usually correspond to build new generating facilities, if possible close to demand centers, or to connect sub-regions through transmission lines. However, the first option is frequently not economically feasible or even possible. Apart from that, the connection of sub-systems can enable the optimal dispatch of power plants or can facilitate the implementation of the economic schedule prepared by centralized market operators, where they exist. Therefore, the TEP problem aims at defining when, where and what equipment (transmission lines, cables or transformers) should be built in order to optimize a predetermined objective (minimizing or maximizing some function) along an extended horizon while enforcing a number of constraints.

The present research aims at identifying new formulations and solution approaches for the TEP problem taking into account the changes and evolutions that are being faced by power systems and that were mentioned in Section 1.1. Accordingly, the main motivations of this Doctoral Thesis are related to four main factors, which are highlighted as follows:

- The difficulties in solving the TEP problem lead to the adoption of relaxed models of the real problem in order to lighten its solution procedures. However, with the fast development of computer processing, new techniques for solving heavy problems have been discussed and developed in the recent literature;
- The active load pattern is changing due the increasing number of electric vehicles, the demand response programs, the increasing of distributed generation, smart grids and microgrids. All these elements will affect the behavior of the electricity demand seen by transmission networks and should be considered in the planning task,
- The RES penetration imposed new challenges for TEP tasks. Now, the mathematical models must incorporate the uncertainties and the intermittent nature of wind and solar generation in future operating costs. Additionally, several wind parks and solar plants can be associated to connection contracts that penalize curtailed renewable generation. This challenge becomes even more complex in hydrothermal systems due to the uncertainty that also affects the hydrological conditions;
- Finally, the unbundling of the electricity sector in several activities poses a number of challenging problems namely because in several areas there are conflicting objectives associated to different stakeholders. These different views and objectives paved the way to the development of new multiobjective tools able to represent this new paradigm. Furthermore, in liberalized electricity systems, investors in generation assets are free to choose when and where to build new generation facilities and the transmission system should be prepared to accommodate different connection decisions and generation patterns.

These motivations are seen as crucial factors towards a sustainable development of the electricity sector in which the decarbonization of generation activities provides business opportunities involving renewable resources and a more active action in the demand through the adoption of several DER technologies. Although this new perspective enables the emergence of new participants and business models, the complexity of the network dramatically increases mainly due the power and the information that flow in multiple directions.

Therefore, this thesis aims at contributing to the development and the adoption of a more adapted formulation regarding the real-world characteristics. This model corresponds to a multiobjective and stochastic optimization formulation which takes into account the active load pattern induced by the DERs elements. Consequently, this research work aims at answering to the four research questions presented below:

i *How to approach the TEP problem in the most realistic way in which the required computational effort does not become prohibitive?*

ii *How the distributed energy resources should be considered on the long-term planning with the aim of taking advantages and benefits for the whole electrical system?*

iii *How the seasonality of water resources and the intermittent nature combined to their low predictability and controllability of wind and solar sources should be addressed and what are their impacts on the long-term planning?*

iv *How the different and conflicting objectives associated to different stakeholders impact the TEP problem and how they should be addressed?*

1.3 Thesis objectives

The goal of the research that was developed is to investigate how decisions regarding the construction of new equipments on the transmission network can be identified and selected considering the DERs penetration and considering the uncertainties coming from hydros, wind and solar generation. This was addressed considering a multiobjective problem in which the reliability and the system total costs are the conflicting objectives to be optimized.

Based on the presented motivation and the mentioned research questions, this Doctoral Thesis addresses the following objectives:

Research objective 1: To compare real and relaxed models with respect to their outputs and required computational effort, as well as to develop search space reduction methods that do not compromise the quality of the final planning solution;

Research objective 2: To analyze the impact of different elements of DERs as well as establishing strategies to take advantage and to benefit from them to the entire electrical system;

Research objective 3: To develop probability planning approaches in which the risks associated to hydro, solar and wind sources are considered and to evaluate their impacts if they are neglected;

Research objective 4: To develop a multiobjective planning tool that considers the maximization of the reliability and the minimization of the total system cost as the conflicting objectives and to provide a set of non-dominated solutions to the decision maker.

Thus, each of these research objectives was addressed in a specific chapter separately, in order to turn the approach more clear and intuitive. Accordingly, after the Introduction and the State-of-the-art and Literature Review, the research objectives 1, 2, 3 and 4 are addressed in Chapters 3, 4, 5 and 6, respectively.

1.4 Structure of the thesis

The research developed within the scope of this PhD thesis was organized in seven chapters, including the present one.

Chapter 1 includes an introduction to transmission expansion planning. The evolution of the electricity sector and planning activities are discussed in Section 1.1, the thesis motivations and research questions are detailed in Section 1.2, the thesis objectives are highlighted in Section 1.3, the structure of this document is presented in Section 1.4 and finally Section 1.5 provides the list of publications held in the framework of this research.

Chapter 2 details the state-of-the-art and literature review regarding the TEP problem. Section 2.1 presents the scope of the chapter. 2.2 provides the general mathematical formulation of the TEP problem. An overview of how the TEP problem is handled in the literature is presented in Section 2.3. The different approaches used in TEP problems are detailed in Section 2.4, the planning costs commonly used in TEP are presented in Section 2.5. Section 2.6 gives the reliability and security consideration in TEP and Section 2.7 provides informations about the economic dispatch usually considered in the planning task. Different considerations about the planning horizon are given in Section 2.8, while the available solution methods are enumerated in Section 2.9 and the objectives related to electricity markets are provided in 2.10. The new challenges of TEP problems are identified in Section 2.11. Finally, coordinated generation and transmission planning insights are presented in 2.12, and some literature insights and gaps are discussed in Section 2.13.

Chapter 3 presents models, algorithms and strategies to deal with TEP problems. Section 3.1 presents the scope of the chapter. Section 3.2 describes the AC and DC optimal power flow models. Section 3.3 discusses some techniques to solve large scale problems and Section 3.4 presents the main constructive heuristic algorithms used in transmission expansion planning problems. Section 3.5 addresses some bio-inspired algorithms to solve these problems. A novel security constructive heuristic algorithm to reduce the search space of the TEP problem and, consequently, the time required to solve it is presented in Section 3.6. Numerical simulations are presented in Section 3.7 and conclusions about the chapter are provided in Section 3.8.

Chapter 4 analyses the impact of the distributed energy resources on transmission expansion planning. Section 4.1 presents the scope of the chapter and Section 4.2 the concepts of distributed energy resources and their applications in the electric system. Section 4.3 brings the different types of distributed generations. Section 4.4 discusses the programs for demand response, the technologies of storage devices are quickly introduced in Section 4.5. The electric vehicles are presented in Section 4.6 and the microgrids are briefly presented in Section 4.7. Section 4.9 includes the corresponding numerical simulations. The main conclusions of this chapter are mentioned in Section 4.10.

Chapter 5 describes the developed probabilistic approach of the TEP problem. Section 5.1 presents the scope of the chapter. Probabilistic planning criteria are provided in Section 5.2 while probabilistic reliability evaluation methods are presented in Section 5.3. The reliability worth assessment are fully addressed in Section 5.4 and the composite system adequacy evaluation in Section 5.5. The probabilistic power generation models are described in Section 5.6. The main tools used in optimization problems under uncertainty is presented in Section 5.7. A risk-based TEP approach is proposed in Section 5.8 and Section 5.9 provides results from the numerical simulations. Finally, the conclusions of this chapter are listed in Section 5.10.

Chapter 6 provides a multiobjective approach to the TEP problem. Section 6.1 presents the scope of the chapter. The Pareto multiobjective optimization concepts are described in Section 6.2 and the solution approaches are presented in Section 6.3. A number of performance evaluation criteria are discussed in Section 6.5. A new multiobjective evolutionary algorithm is proposed in Section 6.6 to address this problem in a more efficient way and Section 6.7 provides the corresponding numerical simulations. The conclusions about the chapter are given in Section 6.8.

Finally, Chapter 7 summarizes the contributions of this research and enumerates the most relevant conclusions. The document ends with an outlook about future research opportunities in this area.

1.5 List of publications

In the last 4 years, during the PhD course, 11 scientific contributions related directly to this thesis were published. In addition, 3 other papers are currently under review. In the next paragraphs these contributions are organized according to the Chapter of this Thesis they are more directly related with.

Chapter 2:

- *State-of-the-art of transmission expansion planning: a survey from restructuring to renewable and distributed electricity markets*. Phillipe Vilaça Gomes and João Tomé Saraiva, submitted to the International Journal of Electrical Power & Energy Systems. It is under review.

Chapter 3:

- *Dealing with models, combinatorial explosion and algorithms on transmission expansion planning*. Phillipe Vilaça Gomes and João Tomé Saraiva, submitted to the International Journal of Electrical Power & Energy Systems. It is under review.
- *Simulated annealing with gaussian probability density function for transmission expansion planning*. Phillipe Vilaça Gomes, U. Porto Journal of Engineering, 2015. 1(1):104–113.
- *Static transmission expansion planning using heuristic and metaheuristic techniques*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE PowerTech, Eindhoven, June 2015.

- *Comparative analysis of constructive heuristic algorithms for transmission expansion planning*. Phillipe Vilaça Gomes and João Tomé Saraiva, U. Porto Journal of Engineering, 2016. 2(2):55–64.
- *Evaluation of the performance of space reduction technique using ac and dc models in transmission expansion problems*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE EEM, Porto, June 2016.
- *Hybrid discrete evolutionary pso for ac dynamic transmission expansion planning*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE ENERGYCON, Leuven, April 2016.

Chapter 4:

- *Transmission system planning considering solar distributed generation penetration*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE EEM, Dresden, June 2017.
- *Impact of Large Fleets of Plug-in-Electric Vehicles on Transmission Systems Expansion Planning*. Phillipe Vilaça Gomes, João Tomé Saraiva, Mario Coelho, Bruno Dias, Leonardo Willer and Candiá Junior, in Proceedings of PSCC, Dublin, June 2018.

Chapter 5:

- *Multiyear transmission expansion planning under hydrological uncertainty*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE PowerTech, Manchester, June 2017.
- *A Stochastic Risk-Based Transmission Expansion Planning for Hydrothermal Systems with Renewable Energy Sources*. Phillipe Vilaça Gomes, João Tomé Saraiva, Leonel Carvalho, Bruno Dias and Leonardo Willer, submitted to the journal International Journal of Electrical Power & Energy Systems. It is under review.

Chapter 6:

- *Multiyear and multi-criteria ac transmission expansion planning model considering reliability and investment costs*. Phillipe Vilaça Gomes, João Silva and João Tomé Saraiva, in Proceedings of IEEE EEM, Porto, June 2016.
- *Hybrid genetic algorithm for multi-objective transmission expansion planning*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE ENERGYCON, Leuven, April 2016.
- *A novel efficient method for multiyear multiobjective dynamic transmission system planning*. Phillipe Vilaça Gomes and João Tomé Saraiva, International Journal of Electrical Power & Energy Systems, 100:10–18, 2018.

Chapter 2

State-of-the-art and literature review

We will make electricity so cheap that only the rich will burn candles.

Thomas Edison, 1879

2.1 Scope

This chapter provides an in-depth review of the TEP literature identifying, classifying and detailing the models, approaches, considerations, concerns, and key tools used in the transmission expansion planning task.

Section 2.2 presents the general mathematical formulation of the planning problem. Section 2.3 presents the main variables that influence the TEP problem and the classification of 75 recent articles published in journals and presented in international conferences addressing the TEP problem.

Section 2.4 details and provides examples of deterministic, uncertain and probabilistic TEP models. Section 2.5 presents how the investment, operation and reliability costs are considered and internalized in TEP problems.

Reliability and security aspects in TEP problems are fully detailed in Section 2.6. Details about the economic dispatch, commonly considered in TEP are presented in Section 2.7

Static and dynamic TEP approaches together with examples are described in Section 2.8. Mathematical, heuristic and metaheuristic models used to solve TEP problems are characterized in Section 2.9.

The restructuring of the electricity markets, the impact of this move on the TEP problem and its different objectives are discussed in Section 2.10.

The new changes on the grid, mainly due DERs are described in Section 2.11. TEP projects and their main objectives and results are provided in Section 2.12 and, finally, the literature insights and gaps are identified and enumerated in Section 2.13.

2.2 Transmission expansion planning formulation

The increasing demand for electricity and the changes in the consumption profile, with the introduction of distributed energy resources, for example, requires a thorough and carefully analysis in the way that the system has to evolve along an extended period of time. In this scope and using a pre-defined list of candidate equipment (transmission lines, cables, transformers, etc.) that can be inserted on the grid, Transmission Expansion Planning (TEP) has the purpose of identifying the ones to be built and their commissioning date to optimize some pre-defined objective function (OF). This function typically corresponds to the investment, operation and/or unreliability costs, while supplying the forecasted demand. Furthermore, the transmission planning analysis must also take into account issues as security and reliability as the well-known N-1 criterion, which makes it a very complex problem. The general formulation of the TEP problem is given by Eq. (2.1) to (2.4).

$$Minimize/Maximize\ OF \tag{2.1}$$

Subject to:

$$Physical\ Constraints \tag{2.2}$$

$$Financial\ Constraints \tag{2.3}$$

$$Quality\ of\ Service\ Constraints \tag{2.4}$$

Physical constraints are associated to the generator and branch capacity limits, financial constraints refer to the maximum amount that is available to be invested in a certain period and the quality of service constraints are for instance related with the maximum value allowed for power not supplied (PNS) in normal or contingency regimes or to maximum reliability indexes.

The decision variables, attributes, criteria, objectives and goals of the single objective TEP problem are defined below based on (Coello et al., 2007):

- *Decision variables*: Generally they are related to equipment candidates for expansion (e.g; transmission lines, cables, transformers);
- *Criteria*: Generally denote evaluation measures and present the global definition of the preference guidelines (e.g; minimize investment costs, maximize reliability);
- *Attributes*: Generally considered as a specific measure of an alternative (e.g; USD, MWh/year);
- *Objectives*: Generally they are related to the direction of the optimization (minimize or maximize);
- *Goals*: They are related to the attribute values and generally they designate potentially attainable levels (e.g. reduction of the emissions by 15%).

2.3 Transmission expansion planning in the literature

The Transmission Expansion Planning problem basically provides information on how a transmission system should evolve over time in the most economical way while maintaining an acceptable risk level. TEP is a complex planning exercise that involves several variables from different nature and behaviors. According to the related literature, this problem can be categorized using six groups of elements that are associated to different models and techniques as illustrated in Fig. 2.1. These elements are as follows: approach, system costs, contingency criteria, reliability, modeling and planning view. Additionally, in the last years, there are at least six other factors that also affect the planning exercise: risk, new changes on the grid, environmental concerns, liberalized power sector, market and the computational burden. The next paragraphs provide some insights on the TEP literature regarding these elements, although these elements are also fully detailed in the next Sections.

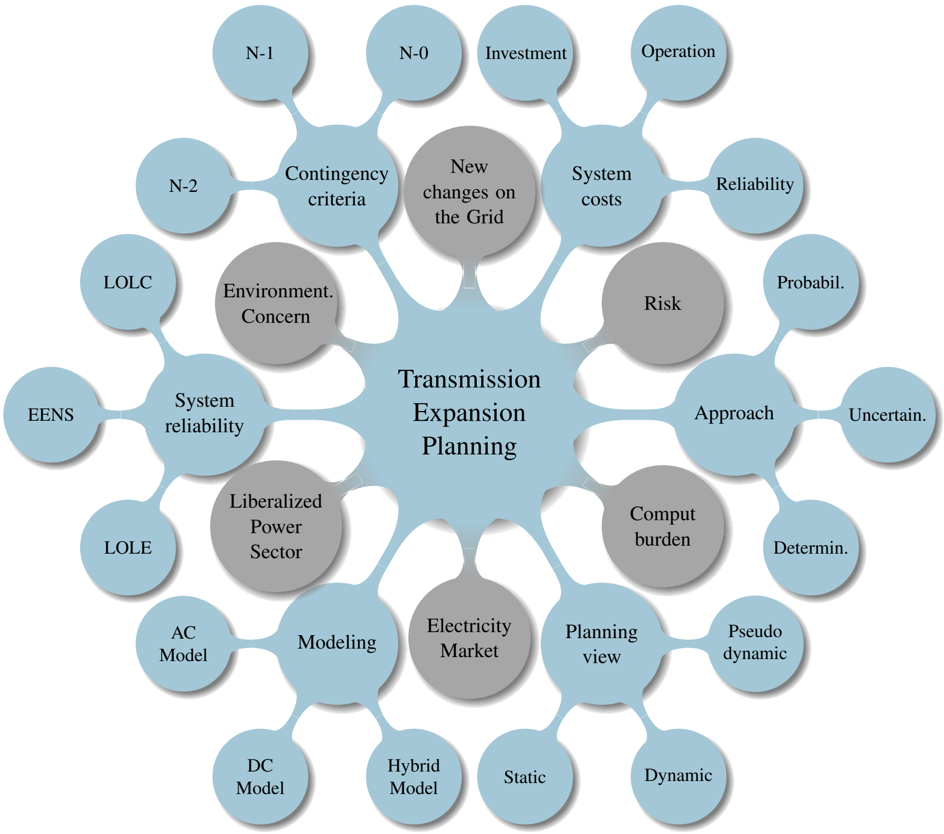

Figure 2.1: Key variables affecting TEP

The TEP **approaches** can be classified as deterministic, probabilistic and under uncertainties. The deterministic models include a set of predicted values for specific variables and these are considered immutable, as generation, demand, market behavior, etc. This model provides a unique expansion planning solution and was used recently in (Wu et al., 2018), (Verma and Mukherjee, 2017) and (Vatani et al., 2017).

In probabilistic approaches, the forecasts admit probabilistic randomness and allow working with different scenarios. Obviously, this approach is closer to reality and its solutions are interpreted as estimates of the true system characteristics. Recently, this approach was used in (Baharvandi et al., 2018), (Rathore and Roy, 2016) and (Qiu et al., 2017).

The third class of approaches admit that some uncertain data is affected by lack of complete knowledge and this incomplete information can, for instance, be modeled with fuzzy numbers, it was used recently in (Zhang and Conejo, 2018a), (Zeinaddini-meymand et al., 2017) and (Gomes and Saraiva, 2018).

TEP usually considers as decision-criterion the **systems costs** which can be represented by only the investment costs as in (Gomes and Saraiva, 2018), (El-Bages and Elsayed, 2017) and (Verma and Mukherjee, 2017), the sum of the investment and future operation costs as in (Zhang and Conejo, 2018a), (Zeinaddini-meymand et al., 2017), (Wu et al., 2018) or even the costs associated to the sum of investment, operation and unreliability costs as in (Baharvandi et al., 2018), (Qiu et al., 2017) and (Nemati et al., 2018).

A worldwide TSO feature is to consider network reliability aspects so that the system deficit due to outage events of transmission equipment is reduced. The N-0 condition is the most basic and crucial condition for the bulk system, that is, the system must meet the load if no equipment is under fault. This condition was considered in (Gomes and Saraiva, 2018), (Zeinaddini-meymand et al., 2017) and (Zhang and Conejo, 2018a). The N-1 **contingency criterion** is widely diffused among the transmission planners and the power industry and it was applied in (da Silva et al., 2017), (Lumbreras et al., 2017) and (Lumbreras et al., 2014). This criterion is usually applied to the worst-case scenario and it means that the system should have enough redundancy in terms of generation facilities, transmission lines and transformers, to ensure a safe operation even when any one of these elements is out of service due to failure.

However, the N-1 criterion corresponds to a deterministic approach that may not ensure the adequate reliability level of the entire system because it does not consider the random behavior of the equipment failures and load fluctuations (Barros et al., 2007) apart from requiring a large computation time. As a result, it is usually applied in TEP problems that use relaxed models in which the holistic view over the entire horizon is disregarded (Poubel et al., 2017). The mentioned random behavior of the equipment and load can only be captured by probabilistic models,as in (Hooshmand et al., 2012), (da Silva et al., 2010) and (Zhao et al., 2009) in which TEP problem is handled considering probabilistic **reliability** indexes as LOLE, LOLC and EENS.

The difficulties in solving the TEP problem leads to the adoption of relaxed **models** of the real problem, for instance using the DC model as in (Baharvandi et al., 2018), (Verma and Mukherjee, 2017) and (Vatani et al., 2017). This model is, by far, the most widely used in the academy and power industry and it is much lighter than the real AC model because it does not consider the reactive power, the branch losses and it assumes that the nodal voltages are at 1.0 pu. However, as a result of the involved approximations, it does not represent accurately the real behavior of an AC grid and, consequently, DC based TEP models underestimate investments and can originate severe violations of grid constraints as mentioned in (Gomes and Saraiva, 2016a), if DC based expansion plans are tested using true AC models. Differently, in (Veeresham et al., 2017), (Hemmati et al.,

2016) and (Wiest et al., 2018) the TEP problem was solved using AC power flow based models thus reducing the gap to reality.

Regarding the **planning view**, the TEP problem can be conducted under a dynamic or a static approach. The multiyear or dynamic nature of TEP problems requires considering in the same run several sub-periods over the planning horizon to identify when and what new equipment (transmission lines, cables or transformers) will be inserted on the grid. This nature brings the benefit of preserving the holistic view over the planning horizon and was applied in (Rad and Moravej, 2017a), (Rad and Moravej, 2017b) and (Rouhani et al., 2014). This means, for instance, that a transmission asset that otherwise should be added later on, can be anticipated if it also solves a bottleneck in a previous period. This holistic view is reported to be able to provide better quality and lower cost expansion plans, but it involves a larger computation effort. The static nature of TEP problems corresponds to a simplified view wherein each period in the horizon is considered at a time and an equipment selected in a given period is taken as available on the next ones as in (Zhang and Conejo, 2018a), (Zeinaddini-meymand et al., 2017) and (Wu et al., 2018).

Regarding the recent factors that can interfere on the planning studies, in any decision that involves **risk** the profit is not the only objective. Therefore, planning under risk also requires analyzing the variations of the attributes to which an utility is exposed as in (Qiu et al., 2017), (Nemati et al., 2018) and (Qiu, 2018). The **new changes on the grid** mainly affecting distribution networks through the deployment of distributed generation, the spread of micro-grids and the increasing penetration of electric vehicles will certainly influence long term transmission planning eventually depending on regional incentive policies (Gomes et al., 2018a). These policies are often motivated by environmental concerns and are used to enhance power systems, turning them less polluting and more environmental friendly, since the International Energy Agency (IEA) indicates that the electricity sector is responsible for about 40% of the total emissions. The papers (Zeinaddini-meymand et al., 2017), (Rathore and Roy, 2016) and (Hemmati et al., 2016) approached TEP considering these new changes on the grid.

The **liberalization of the electricity sector** is also another factor that influences expansion planning activities, since in this context investors in generation are free to decide when and where they will build new capacity. Thus the transmission planners face the "egg and the chicken" dilemma once the generation investors have to know the transmission tariffs to decide where and when they will invest and the transmission planners have to know when and where the generation investors will expand the generation capacity to plan the evolution of transmission and estimate its costs.

The way the electricity sector is regulated – either in terms of traditional vertical utilities or based on competitive market models - has direct influence on planning since the objectives and uncertainties in these two environments are different. In a traditional vertical environment, TEP aims at minimizing investments in new equipments while in a **market based model** transmission companies also aim at facilitating competition among market participants, providing consumers non-discriminatory access to cheap generation and increase the flexibility of system operation. TEP models considering features related to the liberalized electric sector and/or electricity markets are reported in (Zeinaddini-meymand et al., 2017), (Rathore and Roy, 2016) and (Qiu et al., 2017).

Finally, real models and probabilistic approaches that maintain the holistic view over the planning horizon offer more robust and reliable solutions. However, the **computational burden** to use these techniques may become prohibitive, so that different versions of relaxed models are often used. The papers (Poubel et al., 2017), (De Mendonça et al., 2014) and (de Mendonça et al., 2016) conducted the TEP problem applying pre-processing tools that can contribute to reduce the computational effort.

Table 2.1 details the outline review of the recent papers in TEP problems published in journal and in international conferences. The papers were classified taking into account the different variables presented in Fig. 2.1. In this table, the approach is subdivided in deterministic (D), uncertain (U) and probabilistic (P). The reliability and security parameter (Rel/Sec) is classified in N-1 (1), EENS (2) and LOLE (3). The systems costs is divided in investment (I), operation (O) and unreliability costs (R). The recent worries (RW) in the electrical systems is represented by risk (1), new changes on the grid (2), environmental concerns (3), liberalized electric sector and/or electricity market (4) and computational burden (5). The multiobjective approaches are identified by "MO" and the mathematical models classified in "AC" or "DC" regarding the optimal power flow model that is used. Finally the multiyear approach is identified by "MY".

Table 2.1: Outline study of recent papers.

Paper	Approach			Rel/	Costs			R	Method			M	Model		M
	D	U	P	Sec	I	O	R	W	Ma	He	Me	O	AC	DC	Y
(Zhang and Conejo, 2018a)		✓			✓	✓		5		✓				✓	
(Wu et al., 2018)	✓			1	✓	✓		5		✓				✓	
(Gomes and Saraiva, 2018)		✓			✓			5			✓	✓	✓		✓
(Baharvandi et al., 2018)			✓	2	✓	✓	✓				✓			✓	
(Roldán et al., 2018)		✓			✓	✓				✓				✓	✓
(Sun et al., 2018)			✓		✓	✓			✓					✓	
(Nemati et al., 2018)			✓	2	✓	✓	✓	1			✓			✓	
(Wiest et al., 2018)			✓	1				5	✓				✓		
(Qiu, 2018)			✓	2	✓	✓		1-2	✓					✓	✓
(Zhang et al., 2018)	✓			1	✓				✓					✓	✓
(Baringo and Baringo, 2018)		✓			✓	✓			✓					✓	
(Zhang and Conejo, 2018b)		✓			✓	✓			✓					✓	
(Majidi-Qadikolai and Baldick, 2018)		✓		1	✓	✓		5	✓					✓	
(Moreira et al., 2018)		✓		1	✓	✓			✓					✓	
(Dvorkin et al., 2018)	✓				✓	✓		2	✓					✓	✓
(Ziaee et al., 2018)		✓			✓	✓			✓					✓	
(Zeinaddini-meymand et al., 2017)		✓			✓	✓		2-4	✓					✓	
(Gomes and Saraiva, 2017a)		✓			✓			5			✓		✓		✓

Table 2.1 continued from previous page

Paper	Approach			Rel/	Costs			R	Method			M	Model		M
	D	U	P	Sec	I	O	R	W	Ma	He	Me	O	AC	DC	Y
(Verma and Mukherjee, 2017)	✓				✓						✓			✓	
(Vatani et al., 2017)	✓				✓			2-4			✓			✓	
(Veeresham et al., 2017)	✓				✓	✓					✓		✓		
(El-Bages and Elsayed, 2017)	✓				✓						✓			✓	
(Domínguez et al., 2017)	✓				✓	✓			✓					✓	✓
(Qiu et al., 2017)			✓	2	✓	✓	✓	1-2-4			✓	✓		✓	
(da Silva et al., 2017)	✓			1	✓	✓					✓			✓	
(Rad and Moravej, 2017a)		✓			✓	✓	✓				✓			✓	✓
(Rad and Moravej, 2017b)			✓		✓	✓	✓	2			✓	✓		✓	✓
(Moradi et al., 2017)			✓	2	✓		✓				✓	✓		✓	✓
(Lumbreras et al., 2017)		✓		1	✓	✓			✓					✓	✓
(Poubel et al., 2017)	✓			1	✓	✓		5		✓				✓	✓
(Jadidoleslam et al., 2017)			✓	2	✓			1			✓	✓		✓	✓
(Aguado et al., 2017)	✓				✓	✓		2			✓			✓	
(Javadi and Esmaeel Nezhad, 2017)			✓		✓	✓					✓			✓	
(Gomes and Saraiva, 2017b)	✓			2	✓			2			✓		✓		✓
(de Oliveira et al., 2017)	✓				✓			5			✓			✓	✓
(Oliveira et al., 2017)	✓				✓			5			✓			✓	✓
(Li et al., 2017)		✓			✓	✓			✓					✓	✓
(Ugranli and Karatepe, 2017)		✓			✓	✓		4	✓				✓		
(Zhang et al., 2017)	✓			1	✓	✓		5		✓				✓	✓
(Dominguez et al., 2017)	✓			1	✓	✓		5	✓					✓	✓
(Zhan et al., 2017)		✓			✓	✓		5	✓					✓	
(Dehghan et al., 2017)		✓			✓				✓					✓	
(Bagheri et al., 2017)			✓		✓	✓			✓					✓	✓
(Moreira et al., 2017)		✓		1	✓	✓		3	✓					✓	
(Tohidi et al., 2017)			✓	3	✓	✓		4		✓				✓	✓
(Ploussard et al., 2017)	✓				✓	✓				✓				✓	
(Ugranli et al., 2017)		✓			✓	✓			✓				✓		
(Rathore and Roy, 2016)			✓		✓	✓		2-4			✓			✓	
(Guerra et al., 2016)	✓				✓	✓		3-4		✓				✓	✓
(Hemmati et al., 2016)			✓	3	✓	✓		4			✓		✓		✓

Table 2.1 continued from previous page

Paper	Approach			Rel/	Costs			R	Method			M	Model		M
	D	U	P	Sec	I	O	R	W	Ma	He	Me	O	AC	DC	Y
(da Silva et al., 2016)	✓			1	✓						✓			✓	
(Moradi et al., 2016)			✓		✓	✓					✓		✓	✓	✓
(Mínguez and García-Bertrand, 2016)		✓			✓	✓			✓					✓	
(Gomes and Saraiva, 2016a)	✓				✓			5		✓	✓		✓	✓	
(Gomes and Saraiva, 2016b)	✓				✓						✓		✓		✓
(Gomes and Saraiva, 2016c)	✓				✓		✓				✓	✓	✓		✓
(de Mendonça et al., 2016)	✓				✓			5			✓			✓	
(Qiu et al., 2016)			✓		✓	✓		1			✓		✓		
(Sousa and Asada, 2015)			✓		✓			5			✓	✓		✓	
(Ruiz and Conejo, 2015)		✓			✓	✓			✓					✓	
(Tejada et al., 2015)	✓				✓				✓					✓	
(Braga and Saraiva, 2005)	✓				✓	✓	✓				✓	✓		✓	✓
(Gomes and Saraiva, 2015)	✓				✓			5		✓	✓			✓	
(Rouhani et al., 2014)	✓				✓	✓		2		✓					✓
(Florez et al., 2014)		✓			✓			4			✓	✓		✓	
(Lumbreras et al., 2014)	✓			1	✓	✓		5	✓					✓	
(Kamyab et al., 2014)	✓			1	✓	✓		4			✓			✓	✓
(Akbari and Bina, 2014)	✓				✓	✓			✓				✓		✓
(De Mendonça et al., 2014)	✓				✓			5			✓			✓	
(Babić et al., 2013)		✓			✓	✓		4			✓		✓		✓
(Da Rocha and Saraiva, 2013)		✓			✓						✓			✓	✓
(Da Rocha and Saraiva, 2012)	✓				✓						✓			✓	✓
(Akbari et al., 2012)		✓		1	✓	✓	✓	5	✓			✓	✓		✓
(Akbari et al., 2011)		✓		1	✓	✓		5	✓					✓	✓
(Georgilakis, 2010)	✓				✓	✓		4			✓			✓	

Analysing this Table, some patterns can be extracted from this classification. In fact, if these papers are classified regarding the year of publication as *2018*, *2017* and *before 2016* the patterns became easier to be extracted and we can also figure out some trends in this kind of study. The TEP diagram with these three groups is presented in Fig. 2.2.

Thus in the *before 2016* papers (28 publications), the deterministic approach was the most used (58% of the total) while the reliability of the systems was considered in just 21% of the cases. The above mentioned recent worries in the electrical systems were considered in 19 publications, corresponding to almost 68%, and, the metaheuristics were

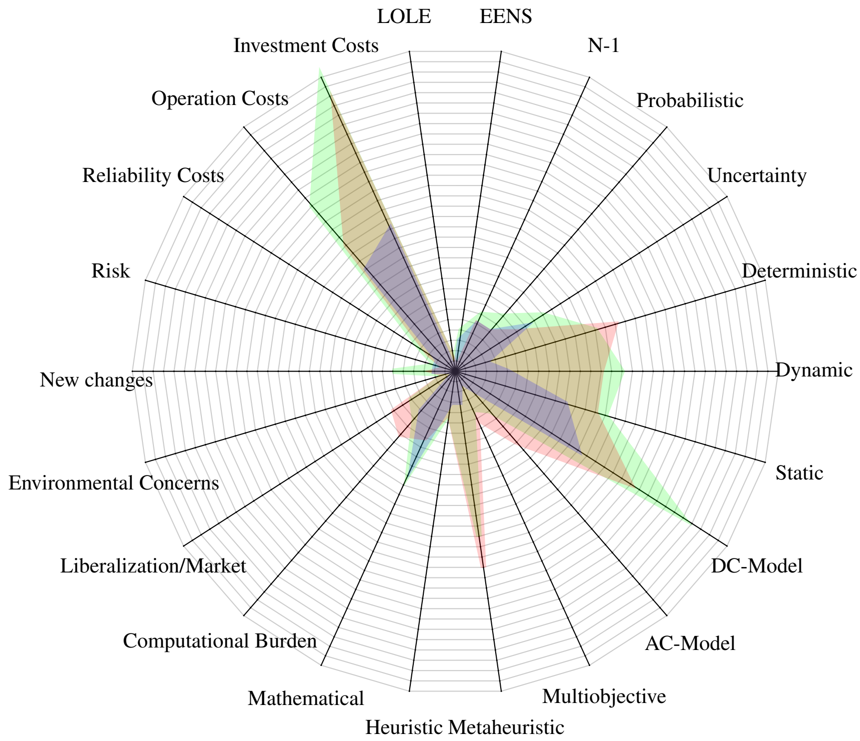

Figure 2.2: TEP diagram considering papers published *before 2016* (red), *2017* (green) and *2018* (blue).

the preferred solution approach in 19 papers while the DC-OPF was used in 20 papers.

An immediate analysis of these results stems from recent worries in the electrical systems - namely risk, distributed energy resources, environmental concerns and liberalization - which can increase the computational effort required in the TEP problem. That's why the deterministic approach and the relaxed DC-OPF model was used so extensively in these papers. Eventually, if the AC-OPF model were used in these circumstances the computational effort would become prohibitive.

On the other hand, as the chosen mathematical approach provides a lot of local optima, metaheuristics were a very convenient choice to handle the TEP task, because they typically include mechanisms to avoid getting stuck in these local optima.

The *2017* group includes 31 papers. In these papers, approaches incorporating uncertainties and probabilistic models start to stand out and correspond to 55%. Furthermore, there is an increase in the reliability consideration, which now corresponds to 36% of the publications. The use of metaheuristics had a small reduction to 51% in contrast to the increased use of mathematical models. The DC-OPF model was used in 84% of the papers.

These above mentioned results, illustrate the same evidence identified before, that is, when the analysis get deeper and stronger (and the computational effort increases), the models also tend to get lighter and relaxed in order to compensate the computational burden and to ensure that the problem keeps scalable.

Regarding the *2018* group, 16 papers are considered. The incorporation of uncertainty and probabilistic models increased dramatically and now it corresponds to 82%, the reliability consideration also got increased to 50%. On the other hand, mathematical models correspond to 63% and the DC-OPF model to 88%.

These results are associated, especially, to the renewable generation, which is considered in the majority of the papers. These resources typically have intermittent and low predictability characteristics that can only be captured by more robust approaches than deterministic, as the uncertainty and probabilistic models. Likewise, the intrinsic characteristics of renewable sources are challenging planners to maintain sufficient levels of reliability, therefore its consideration in these papers has also increased. As the computation burden is too large in these analyses the most adequate way to allow the problem to be scalable is to use the relaxed DC model in the TEP formulations.

2.4 Transmission expansion planning approaches

Transmission expansion planning is strongly dependent on the input information as load growth rate, equipment forced outage rates (FOR), generation matrix profile, schedule for new commissioned transmission lines, substations, power plants, etc. However, this information can be obtained from studies or tasks that may contain some level of uncertainty. Furthermore, renewable generation as wind and solar PV are intermittent and very unpredictable. These units can also be connected to the distribution grids, and, together with electrical vehicles, storages devices and smart grids they can change the conventional generation-transmission-load pattern of the bulk system seen by the transmission planner.

Although traditional deterministic TEP models are much lighter to solve, they are not able to capture the real stochastic behavior of the power system and, in several situations, they can provide underestimated investments and unrealistic transmission plans. These traditional models consider crisp forecasts for important variables such as load, generation and market behavior which do not match with the electrical system reality. Nevertheless, these models are very important in the correspondent literature because they allows addressing other important aspects of planning (with a lither computational effort), such as:

- choosing interesting routes to TEP, reducing the search space and, consequently, the computational burden, as in (de Mendonça et al., 2016) and (Wu et al., 2018);
- Identifying the impact of solar distributed generation in the planning tasks, as in (Gomes and Saraiva, 2017b);
- Addressing other unusual solutions in planning such as network reconfiguration and repowering in order to explore their impacts, as in (Tejada et al., 2015).

The stochastic behavior of the power system has drawn increasing attention in the last years, mainly in TEP models. This nature can be captured by probabilistic models when the uncertainties considered can be represented through probability theory. Some examples of uncertainties that can be treated using probabilistic models are:

- Electricity demand level, as in (Baharvandi et al., 2018);

- Wind generation, as in (Rathore and Roy, 2016);
- Solar generation, as in (Kayal and Chanda, 2015);
- FOR of equipments, as in (Qiu et al., 2017).

The stochastic behavior of power systems can also be captured by uncertainty models, when the uncertainties considered can not be represented by probability theory, as for instance:

- Strategy in the market participants, as in (Zeinaddini-meymand et al., 2017)
- Growth rate of the electricity demand, as in (Da Rocha and Saraiva, 2013);
- Hydrological conditions, as in (Gomes and Saraiva, 2017a);
- Generation fuel costs, as in (Baringo and Baringo, 2018).

2.5 Equipment considered in the planning task

TEP usually takes into account considerations about the investment costs in new equipment, even though other objective besides the minimization of the system costs are involved. In fact, in the large majority of the TEP studies, the investment costs are considered as the main or unique decision-making driver as in (Gomes and Saraiva, 2018), (El-Bages and Elsayed, 2017), (Sousa and Asada, 2015), (da Silva et al., 2016) and (Florez et al., 2014) or even as a part of the decision-making as in (Qiu et al., 2016), (Ugranli et al., 2017), (Ploussard et al., 2017), (Tohidi et al., 2017) and (Moreira et al., 2017).

The equipment that is usually considered include AC transmission lines, cables and transformers. However there are some special elements that are receiving increasing attention from the scientific community (Lumbreras and Ramos, 2016), for instance:

- **High-Voltage Direct-Current (HVDC)** - The interest in HVDCs systems has increased considerably in the last years because they are associated to several advantages, namely they can carry more power per conductor when compared to AC systems, they provide direct control of power flows to the operator and they also provide an increased stability to the system (Domínguez et al., 2017). HVDC links are considered in TEP problems, for instance, in (Blanco et al., 2011);
- **Flexible Alternating Current Transmission Systems (FACTS)** - As for HVDC systems, FACT devices have also been considered more and more in recent years, mainly because they can be used conveniently to overcome congestion problems in the transmission system without increasing the connection capacity (Lumbreras and Ramos, 2016). FACTs devices are considered in TEP problem, for instance, in (Blanco et al., 2009);
- **Fixed series compensation (FSC)** - This equipment has been gaining more attention due to its capacity of reducing the transmission line reactance and, consequently optimizing the performance of long transmission lines. The mentioned improvement is related with the power transfer capacity, power system stability and voltage regulation. This equipment is considered, for instance, in (Rahmani et al.,

2013).

2.6 Reliability consideration

Reliability is a very important element that is very often considered in TEP analysis and that presents a clear relation with the risk of the system not being able to supply the demand. Reliability and risk are quantified using different measures which represent the same evidence, in fact, lower risk is typically related with high reliability and vice-versa. In a general way, reliability can be defined as the ability of the system to perform its function in adequate conditions, while risk can be defined as the inability to execute that function.

There are two basic parameters that represent reliability. In one hand, the adequacy is related to the capacity of the system to supply the electric demand considering all the operational constraints. On the other hand, security is related to the capacity of the system to respond to a disturbance that affects a generation or transmission facility. Therefore, adequacy refers to the static side of reliability while the security corresponds to the dynamic one (Li, 2011).

TEP tasks usually consider both adequacy and security. The adequacy parameter is considered using the forecasted peak load, that is, the system is designed to operate properly when the peak load occurs along the planning horizon (considering that the demand is inelastic). On the other hand, the security issue is commonly taken care by the N-1 contingency criterion.

The classical TEP approaches use deterministic indices to assess the reliability. However, in the last years, some probabilistic parameters have been considered in the TEP problems as a way to complement (not to replace) the deterministic approaches (Li, 2011), as:

- **Adequacy indices**: Probability of Load Curtailments (PLC), Expected Frequency of Load Curtailments (EFLC), Expected Duration of Load Curtailments (EDLC), Average Duration of Load Curtailments (ADLC), Expected Demand Not Supplied (EDNS) and Expected Energy Not Supplied (EENS);
- **Security Indices**: Probability of System Instability (PSI) and Risk Index (RI).

These probabilistic indices are fully detailed in Section 4.3 of the Chapter 4.

TEP considering the single contingency criterion is handled in (Wu et al., 2018), (da Silva et al., 2017), (da Silva et al., 2016), (Lumbreras et al., 2014) and (Poubel et al., 2017). TEP considering probabilistic reliability indices is handled in (Baharvandi et al., 2018), (Qiu et al., 2017), (Nemati et al., 2018), (Hemmati et al., 2016) and (Moradi et al., 2017).

2.7 Economic dispatch

The system dispatch is very often considered in the TEP problem, even if the operation cost of the system for future operation scenarios is not one of the objectives to be optimized. In fact, the simpler versions of the TEP problem that only take into account the minimization of the investment costs, have to evaluate the future dispatch of the candidate solutions in order to assure that the system can operate properly respecting the equipment capacity restrictions.

When only the investment cost is used, the system dispatch usually considers the peak load level. However, when operation or reliability costs are associated with the objective function, the system dispatch usually considers a more detailed representation of the electric demand, which can be considered hourly or by a number of load blocks, each of them corresponding to the average load along a predetermined period (daily, weekly, monthly or annual).

However, TEP is a problem that typically demands a high computational effort and therefore the level of detail of the dispatch is usually approached using load blocks, neglecting hydrothermal coordination and short-term constraints like ramps (Lumbreras and Ramos, 2016).

In addition, the dispatch can be conducted through two models, namely the DC model and the AC model, which are briefly described below:

- **AC Optimal Power Flow Models (AC-OPF)**: These are the natural models for an AC grid and they are able to incorporating voltage limits, stability considerations, accurate evaluation of transmission losses and reactive power flows. However, this kind of model is related to a high computational effort due its non linearities and so it has only begun to be used in TEP problems in recent years with the increase of computer processing;
- **DC Optimal Power Flow Models (DC-OPF)**: This corresponds to a relaxed model of the AC-OPF, that considers the Kirchhoff's first law and a linear version of the second one. The DC model offers a good trade off between an accurate technical description and the computational burden, and therefore has been extensively applied in TEP formulations. Some simplifications are admitted as valid in the DC model as the branch resistances are negligible compared to branch reactances, admittances to ground are negligible, bus voltages are near their nominal value and set at 1 pu and the phase angle differences between adjacent nodes are small.

TEP formulations using the DC-OPF models are available in (Majidi-Qadikolai and Baldick, 2018), (Oliveira et al., 2017) and (de Oliveira et al., 2017). TEP studies using AC-OPF models are conducted in (Wiest et al., 2018), (Akbari and Bina, 2014) and (Akbari et al., 2012).

Finally, the study conducted in (Gomes and Saraiva, 2016a) reported that DC based TEP models are likely to underestimate investments and can originate severe violations of grid constraints if DC based expansion plans are tested using true AC models.

2.8 Planning horizon

Transmission Expansion Planning can be addressed statically or dynamically. In the first option, the problem is conducted to determine where the transmission network should be expanded to meet the future demand admitting a single planning period. This means that there is no consideration of when the selected equipment should be inserted on the grid, which makes the required computational effort lighter. Thus, the planning horizon is taken into account at once (one-shot).

On the other hand, dynamic approaches take the planning horizon in a holistic way. The planning horizon is subdivided in several periods (commonly each of them having one or two years) and the investment decision process is performed over these sub-periods, even though all the planning horizon is taken as a whole. It is noteworthy that the multiyear consideration of investment decisions requires a heavier computational effort, that often becomes prohibitive. Nevertheless, this approach can provide better solution plans because it is possible to obtain solutions that anticipate the connection of some pre-selected equipment to solve a bottleneck or even postpone some equipment in order to reduce the involved costs in terms of their present value.

Fig. 2.3 illustrates the two approaches to the planning horizon. In the static TEP, the information about the system (load, generation, equipment, etc) is only considered at the planning horizon in one-shot, thus, the solution plan presents a list of equipment selected in order to optimize some pre-defined objective (minimize investment cost, total system cost, etc).

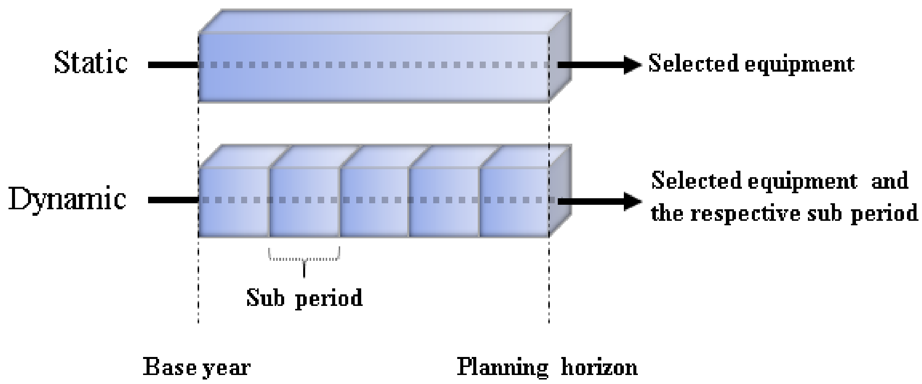

Figure 2.3: Static and dynamic approaches.

On the other hand, in dynamic TEP models, the mentioned information is handled over the sub-periods of the planning horizon and the solution plan presents a list of candidate equipment with the respective period in which the equipment has to be inserted on the grid.

Some authors consider the static option in their studies, as in (Georgilakis, 2010), (Sousa and Asada, 2015), (Ruiz and Conejo, 2015) and (Mínguez and García-Bertrand, 2016).

Differently the dynamic option was used in (Akbari et al., 2012), (Da Rocha and Saraiva, 2012), (Kamyab et al., 2014) and (Domínguez et al., 2017).

Lastly, a sequential static approach can also be adopted in order to reduce the computational burden required in the dynamic approach and to improve the results obtained by the purely static approach. This model was used in (Serna et al., 1978) and it is usually termed as ”pseudo-dynamic TEP”, though it is rarely used in recent years.

2.9 Solution methods

Solving the TEP optimization problem is an arduous task since it has some special features that increase its complexity:

- The search space is non-convex so that several solution algorithms may converge to local optima;
- In some cases there are isolated smaller systems, which may lead to convergence problems;
- The problem typically has an integer nature leading to the combinatorial explosion of investment alternative plans.

These characteristics demand powerful methods generally using high computational effort to identify good quality plans. In fact, in this kind of problem, just being able to identify a feasible solution is sometimes seen as a good result to be commended.

Thus, these characteristics correspond to the main difficulties in developing high-performance tools in terms of speed, efficiency and robustness to solve the TEP problem. The literature of this area includes a variety of models and tools to solve it. These models and tools can be organized in three classes as follows:

- **Classical Optimization Algorithms** - they use decomposition techniques and generally find global optimal solutions for a relaxed version of the original integer problem in which integer investment alternatives are substituted by continuous variables. However, they usually require a large computational effort and therefore they display difficulties to address the expansion of medium and large systems as most of real transmission systems are. In some cases, they can also display convergence problems. This type of methods is used for instance in (Zeinaddini-meymand et al., 2017), (Domínguez et al., 2017), (Ruiz and Conejo, 2015), (Lumbreras et al., 2017), (Tejada et al., 2015), (Mínguez and García-Bertrand, 2016), (Lumbreras et al., 2014), (Akbari et al., 2011), (Akbari et al., 2012), (Akbari and Bina, 2014), (Wiest et al., 2018);
- **Constructive Heuristics Algorithms (CHAs)** - these approaches correspond to simplified procedures that are suitable to identify feasible solutions for complex problems using efficient and easily applied algorithms. They have little computational effort, but they rarely find the optimal global solution, especially if one is addressing real transmission networks. This type of approach was applied in (Zhang and Conejo, 2018a), (Wu et al., 2018), (Rouhani et al., 2014), (Guerra et al., 2016), (Roldán et al., 2018), (Poubel et al., 2017), (Gomes and Saraiva, 2015), (Gomes and Saraiva, 2016a), (Zhang et al., 2017);

- **Metaheuristics** - they are heuristic techniques that are enhanced with particular search procedures in most cases inspired in natural mechanisms. They are especially suited to solve complex and combinatorial problems usually identifying optimal or sub-optimal solutions even for large systems. However, they are typically associated to large computational efforts. This approach is used in (Baharvandi et al., 2018), (Gomes and Saraiva, 2018), (Verma and Mukherjee, 2017), (Gomes and Saraiva, 2017a), (Vatani et al., 2017), (Veeresham et al., 2017), (Rathore and Roy, 2016), (El-Bages and Elsayed, 2017), (Qiu et al., 2017), (Nemati et al., 2018).

The major difference between heuristic and metaheuristic algorithms is that heuristic models are problem-dependent techniques, which means that they are usually adapted to the problem under consideration in order to take advantage of the identified idiosyncrasies. As they are commonly very greedy they usually get trapped in a local optimum. On the other hand, metaheuristic models are problem-independent techniques, which means that no particular knowledge of the problem is necessary. They often overcome the problem of being trapped in local optima by admitting worse solutions in an iteration as a way to possibly find a better solution in the new neighborhood in a later iteration.

In the last years, several bio-inspired metaheuristics were used to solve the TEP problem, and generally this kind of approaches is reported to produce good results. Some examples of TEP formulations handled by bio-inspired algorithm are:

- *Ant colony*, as in (da Silva et al., 2010);
- *Artificial immune system*, as in (Rezende et al., 2009);
- *Artificial neural network*, as in (Al-Saba and El-Amin, 2002);
- *Echolocation of bats algorithm*, as in (Oliveira et al., 2017);
- *Bee algorithm*, as in (Kuo et al., 2010);
- *Firefly algorithm*, as in (Mendonca et al., 2013);
- *Frog leaping algorithm*, as in (Eghbal et al., 2011);
- *Genetic algorithm*, as in (Romero et al., 2007);
- *Particle swarm optimization*, as in (Gomes and Saraiva, 2015);
- *Evolutionary particle swarm optimization*, as in (Gomes and Saraiva, 2016b);

2.10 Electricity markets and objectives

Power systems have experienced many changes over the last years, as presented in Section 1.1, namely the unbundling of traditional utilities and the introduction and development of competition in several segments. Thus, some key words are commonly used in the correspondent literature to describe several approaches regarding the electricity market reform (da Rocha, 2011). Some of these key words are as follows:

- *restructuring* which is commonly used to refer to the reorganization of the roles of market players;

- *liberalization* that refers to the change of the electricity market towards competition in some or all segments with the increase of the number of players;
- *deregulation* was originally designated for the process of implementation of market mechanisms in the electric sector, although this name may sound (incorrectly) as a process of reducing or eliminating the regulatory mechanisms applied to the industry. For this reason, this term has been used less and less in the literature and it is sometimes substituted by re-regulation as a way to transmit the idea of a new body of laws, rules and regulations to enable competition.

Thus, transmission expansion planning problems should be treated according to the environment in which the power system is, that is, traditional vertically integrated or restructured environments have a direct influence on how the planning studies will be developed, since the objectives and uncertainties in these two environments are different.

Generally, in traditional environments, TEP aims at meeting the future demand, commonly considering security and reliability constraints, in order to minimize investments in new equipment. On the other hand, in restructured environments, the objectives of the different stakeholders in transmission expansion can be:

- Encouraging and facilitating competition among electric market participants, as in (Buygi et al., 2004b);
- Providing non-discriminatory access to cheap generation for consumers, as in (Buygi et al., 2004a);
- Alleviating transmission congestion, as in (Dehghan et al., 2011);
- Minimizing the risk of investments, as in (Roh et al., 2009);
- Minimizing the investment and operation costs, as in (Zhang and Conejo, 2018a);
- Allowing better voltage level regulation, as in (Jalilzadeh et al., 2008);
- Increasing the reliability of the network, as in (Gomes and Saraiva, 2016c);
- Increasing the flexibility of the system, as in (Zhao et al., 2009);
- Minimizing the environmental impacts, as in (Unsihuay-Vila et al., 2011);

The uncertainties are present in the restructured environment much more incisively than in the traditional environment since the information about the generation expansion planning are no longer intrinsic to the entity that is conducting the TEP problem. In addition, with the penetration of intermittent energy sources, the transmission network must be able to accommodate multiple different dispatch patterns.

2.11 New changes on the grid

The recent advent of changes namely in the distribution networks related with the increasing presence of distributed energy resources as distributed generation, the development of micro and smart grids and the increasing number of electric vehicles must also be incorporated in long-term expansion planning methodologies (Gomes and Saraiva, 2017b). In the next paragraphs, these elements are presented as well as some impacts reported in the literature:

i **Distributed Energy Resources (DERs)** - There are several definitions for DERs in the literature. For instance, the North American Electric Corporation (NERC) defines DERs as any resource on the distribution system that produces electricity (NAERC, 2017), the New York Independent System Operator (NYISO) defines it as any power generation and storage devices also located on the distribution grid operated for the purpose of supply the local load while the New York Public Service Commission (PSC) defined DERs as NYISO but including energy efficiency and demand response (DNV, 2014). Among the definitions that are available in the literature, they all have in common the ”behind-the-meter” behavior, which means that DERs are not connected to the bulk system. In this Doctoral Thesis, the term DERs is related to any resource located on the distribution grid created or sized to meet the local demand, fully or partially;

ii **Distributed Generation (DGs)** - According to the National Electricity Agency (ANEEL) of Brazil, DG is an electricity generation plant, based on hydro, solar, wind, biomass or qualified co-generation, with installed power less than or equal to 5 MW (3 MW for hydraulic sources) (Gomes et al., 2018a). DGs can reduce the local load when connected to the distribution grid and, consequently, can reduce the congestion in transmission networks and defer investments in transmission equipment. On the other hand, when DGs reaches bigger levels, DG agents can be involved in the spot market and trade the electricity through the transmission grid, increasing the congestion in the transmission lines which may demand for more investments in transmission equipment (Zhao et al., 2011). For this reason, DGs must be taken into account in the TEP tasks. TEP considering DGs penetration is handled in (Gomes and Saraiva, 2017b), (Zhao et al., 2011) and (Rouhani et al., 2014);

iii **Microgrids (μGs)** - Microgrid is a system with interconnected loads and distributed energy resources associated to local and centralized control systems that has its boundaries clearly defined. It operates as a single controllable aggregated load that can eventually be disconnected from the main grid to operate in an island mode. The impact of microgrids in transmission and generation investments was analysed in (Khodaei and Shahidehpour, 2013). In this research the authors showed that μGs can be very cost-effective in reducing investment cost while increasing the reliability of the grid;

iv **Plug-in-electric vehicles (PEVs)** - The electrification of the transport sector conjugated with the decarbonization of the electricity industry is one of the most important keys to achieve meaningful reductions of carbon dioxide emissions. However, the increasing number of PEVs changes the daily system electricity demand and surely it must be considered when planning both distribution and transmission grids. The projections for the penetration of PEVs are increasingly positive especially in countries such as the USA, Germany, Spain, UK, Norway, Portugal and Greece (Hatziargyriou et al., 2013). For instance, the Electric Power Research Institute (EPRI) expects that by 2020 up to 35% of the new USA vehicles will be electric (EPRI, 2007). PEVs can be seen as controlled loads and/or as controlled sources and these characteristics can be used in a profitable way to help accommodating increasing amount of electricity injections from intermittent sources. The impact of large fleets of PEVs on TEP was assessed in (Rathore and Roy, 2016) and (Gomes et al., 2018b).

v **Demand Response (DRs)** - is a temporary change of the consumption pattern of a group of end users as a reaction to a change, in general an increase, in electricity tariffs. It is generally expected that the consumption is optimized through a peak clipping with the correspondent valley filling. This change of pattern occurs only in flexible/interruptible loads, that is, loads that can be smoothed over a period or even disconnected.As TEP traditionally uses the forecasted peak load, which is viewed as the worst-case scenario, to quantify new investment requirement, DR programs can be an excellent alternative to postpone investment in the transmission equipment. TEP considering DRs was analysed in (Li et al., 2015) and (Hajebrahimi et al., 2017).

2.12 Coordinated generation and transmission planning

Generation planning aims at selecting the capacity, technology and commissioning time of new generation units on the system. On the other hand, the transmission planning determines where and when new equipment should be inserted in order to meet the electric demand, taking into account reliability indexes and network security.

On certain occasions, generation expansion planning must be taken into consideration along with the transmission expansion planning studies and exercises. Generally, transmission companies have to consider inputs from generation expansion planning namely to perform TEP studies in a more effective and adequate way. In some countries, as Brazil, there are state entities in charge of preparing reference expansion plans for generation and then specific auctions are opened to allocate specific generation projects to generation companies. In these cases, the use of models that consider some level of coordination between the expansion of generation and transmission is justified.

However, in other countries restructuring was implemented in a more complete and deeper way so that generation companies take decisions individually based solely on the maximization of their profits eventually requiring some administrative authorization to install new capacity. In these cases, centralized studies are not applicable. Nevertheless, even though these coordinated studies are implemented directly, they can provide valuable information both to transmission network planners and to generation investors, particularly regarding the allocation of renewable generation targets (Lumbreras and Ramos, 2016) and the determination of tariffs related to the use of transmission networks.

Regarding the mathematical formulation for the coordinated generation and transmission expansion planning, GTEP problem, it should be noticed that it is a complex optimization task that has nonlinear, non-convex and mixed-integer nature. As examples, this problem was addressed in Lee et al. (2006), Javadi et al. (2014), Tor et al. (2008), Roh et al. (2009) and Seddighi and Ahmadi-Javid (2015).

2.13 Literature insights and identified gaps

The presented literature review addresses many aspects of transmission expansion planning variants, uncertainty and reliability issues as well as its relations with other problems. This deep study allowed obtaining important insights for the conduction of this PhD research, namely:

i It allowed to understand the main modeling techniques and computational complexities of the TEP problems;

ii It described how uncertainty issues affecting the future condition of the power system can be incorporated in the TEP models;

iii It showed how the decision-making is conducted over the different objectives demanded by many stakeholders;

iv It revealed that the system reliability analysis over deterministic and probabilistic approaches are used together to reach better results;

v It allowed to clarify how the solution techniques are applied in order to achieve good solutions in adequate time.

The thorough literature review also enabled identifying some gaps which appear to have not been fully addressed by the scientific community, namely:

i It is still recent and scarce the literature that addresses the TEP problem with complete power flow models (with correct representation of losses, variation of bus voltages and reactive power) and that considers the planning holistic view (in terms of distributing investment decisions along the planning horizon), which demands a very high computational cost. However, there are no qualitative or quantitative studies reporting the improvements from these approaches in the planning exercises with a proper justification for the larger computational effort;

ii Recent advances in the spread of distributed energy resources can modify the power flow patterns in transmission and distribution networks, mainly at the transmission-distribution boundary. These impacts are scarcely addressed in the literature and need to be modeled and assessed.

iii Many studies already incorporate uncertainties related with renewable energy into the TEP problem. However, most of them only use peak load values, which are seen as the worst case, to quantify investments in new equipment for the transmission network. However, it is not clear if such peak load scenarios are enough and if the associated investment decisions are sufficient for the system to operate properly for any other scenario. Should scenarios with large demand, but smaller than the peak load, associated with a low renewable production (eventually originating more stressed operation conditions for the transmission network) also be considered?

iv Finally, a number of studies have also been identified that address the unbundling of the electricity sector. However, in these analyzes most studies consider only one objective, contrary to the recent and diverse wishes of several stakeholders;

Summarizing, although there are substantial research works on transmission expansion planning in the literature, there are few papers that bring insights on how complex and time-consuming models can improve the solution plans or how renewable energy uncertainties and multiobjective approaches can impact on the final plan quality.

Therefore, this Doctoral Thesis was conducted towards this direction, that is aligned to the research questions and objectives of this research that were enumerated in Chapter 1.

Chapter 3

Dealing with models, combinatorial explosion and algorithms on transmission expansion planning

> It doesn't matter how beautiful your theory is, it doesn't matter how smart you are. If it doesn't agree with experiment, it's wrong.
>
> *Richard P. Feynman*

3.1 Scope

In this chapter the different mathematical models available in the TEP literature will be discussed, as well as the different algorithms used in its solution. Section 3.2 presents the AC-OPF and DC-OPF based models, used in the TEP problem.

Section 3.3 presents two very effective techniques to reduce the computational time required to solve TEP problems, namely subsection 3.3.1 describes the search space reduction techniques and subsection 3.3.2 addresses the parallel computing technique.

Section 3.4 presents the main Constructive Heuristic Algorithms (CHA) used in the TEP literature. Thus, the Garver CHA is discussed in 3.4.1, the Least Effort CHA is presented in 3.4.2, the Least Load Shedding CHA is addressed in 3.4.3 and finally, the most modern CHA algorithms entitled Sigmoide and Portfolio of indices are presented in sections 3.4.4 and 3.4.5, respectively.

Section 3.5 includes important discussions about bio-inspired metaheuristics used to solve the TEP problem. Subsection 3.5.1 presents the genetic algorithms, subsection 3.5.2 presents the particle swarm optimization and subsection 3.5.3 its evolutionary version.

Finally, Section 3.6 presents the proposed security CHA and Section 3.7 presents four cases of simulations regarding the content of this chapter. Section 3.8 discusses the main conclusions about these results.

3.2 Optimal power flow models

TEP problems usually require information about the optimal system dispatch because the system should be designed to meet the forecasted electric demand over a planning horizon considering all the system capacity and operation constraints. This typically means dispatching the generators in a pre-defined merit-order, usually zero marginal cost renewable units followed by the cheaper conventional generators.

There are two different ways to consider the forecasted electric demand, i.e; modeling the load in an elastic or an inelastic way. In the first approach, the load is controlled considering different signals such as the market price. Consequently, load shedding is an option for the transmission planners that will then have to consider a cost for the generation deficit. In the inelastic approach, the demand is considered fixed and it must be supplied, and as a result load shedding happens only in scarcity cases that can be overcome otherwise (Majidi-Qadikolai et al., 2017).

In either case, the optimal dispatch is an extremely important module in TEP studies since it provides the planner with information about the future system state when meeting the forecasted electric demand. The most common mathematical model for optimal dispatch in use in TEP problems is the DC-OPF which corresponds to a relaxed and linearized version of the AC-OPF.

In this Doctoral Thesis we use the MATPOWER tool (Zimmerman et al., 2011) to assist the OPF calculations. However, as new equipments are inserted or removed from the grid, the model must be adapted to be able to consider these changes. Thus, the AC and DC OPF models used in this research are fully described in the next subsections.

3.2.1 AC-OPF model

The AC model is the natural model to represent an AC grid because it takes into account the reactive power, losses and voltage limits on the bars. This complete nature makes this model more adequate and realist to reflect the operation conditions of the network and therefore to estimate the operational cost of a power system. In whatever way, the AC model introduces a challenging mixed integer, non-convex and non-linear nature to the problem and so several approaches can be used to turn it more tractable.

The full AC based dispatch model, for a predefined load block, is described by (3.1) to (3.10).

$$Minimize \sum_{ger=1}^{nger} F_{ger}(P_G^{ger}) + \sum_{bus=1}^{nbus} (1-\alpha_{bus}) P_D^{bus} . C_{def}^{bus} \tag{3.1}$$

Subject to:

$$P(V,\Theta,n)_{bus} - P_G^{bus} + \alpha_{bus} . P_D^{bus} = 0 \tag{3.2}$$

$$Q(V,\Theta,n)_{bus} - Q_G^{bus} + \alpha_{bus}.Q_D^{bus} = 0 \tag{3.3}$$

$$P_{G_{min}}^{ger} \leq P_G^{ger} \leq P_{G_{max}}^{ger} \tag{3.4}$$

$$Q_{G_{min}}^{ger} \leq Q_G^{ger} \leq Q_{G_{max}}^{ger} \tag{3.5}$$

$$V_{min}^{bus} \leq V^{bus} \leq V_{max}^{bus} \tag{3.6}$$

$$(N + N^0)S^{from} \leq (N + N^0)S^{max} \tag{3.7}$$

$$(N + N^0)S^{to} \leq (N + N^0)S^{max} \tag{3.8}$$

$$0 \leq n \leq n^{max}, n \in \mathbb{Z}_+ \tag{3.9}$$

$$0 \leq \alpha \leq 1 \tag{3.10}$$

In this formulation, Eq. (3.1) is the objective function to be minimized in which the first part corresponds to the total generation costs and the second part to the deficit cost due power not supplied. Eq. (3.2) and (3.3) are the real and reactive nodal power balance equations. To ensure that at least one solution exists for the AC-OPF, the loads are considered dispatchable that is, the loads are modeled with a flexibility variable, α, which means the problem has enough flexibility to reduce the demand in node *bus* if this is required to maintain feasibility. Additionally, if an active load shedding is needed, then the reactive demand is also reduced in the same proportion to keep the power factor unchanged. Eq. (3.4) and (3.5) are the real and reactive power limit constraints, Eq. (3.6) is the voltage limit constraint, Eq. (3.7) and (3.8) ensure that the apparent power flow in each branch complies with the transmission limits. Eq. (3.9) imposes the maximum number of new equipment (integer variable) to be inserted in a right-of-way and Eq. (3.10) imposes the load reduction flexibility range.

The values of the nodal injected powers P(V,Θ,n) and Q(V,Θ,n) are calculated by Eq. (3.11) and (3.12):

$$P(V,\Theta,n) = V_i.\sum V_j.[G_{ij}(n).cos\Theta_{ij} + B_{ij}(n).sin\Theta_{ij}] \tag{3.11}$$

$$Q(V,\Theta,n) = V_i.\sum V_j.[G_{ij}(n).sin\Theta_{ij} - B_{ij}(n).cos\Theta_{ij}] \tag{3.12}$$

In this formulation, the branch conductance G_{ij} and susceptance B_{ij} are calculated by Eq. (3.13) and (3.14):

$$G_{ij} = \begin{Bmatrix} -(n_{ij}.g_{ij} + n_{ij}^0.g_{ij}^0), \forall i \neq j \\ \sum_{j\epsilon\Omega_i}(n_{ij}.g_{ij} + n_{ij}^0.g_{ij}^0), \forall i = j \end{Bmatrix} \tag{3.13}$$

$$B_{ij} = \begin{Bmatrix} -(n_{ij}.b_{ij} + n_{ij}^0.b_{ij}^0), \forall i \neq j \\ b_{ij}^{sh} + \sum_{j\epsilon\Omega_i}[n_{ij}.(b_{ij} + b_{ij}^{sh}) + n_{ij}^0.(b_{ij}^0 + b_{ij}^{sh^0})], \forall i = j \end{Bmatrix} \tag{3.14}$$

The apparent branch flows S^{from} and S^{to} are given by:

$$S_{ij}^{from} = \sqrt{(P_{ij}^{from})^2 + (Q_{ij}^{from})^2} \tag{3.15}$$

$$S_{ij}^{to} = \sqrt{(P_{ij}^{to})^2 + (Q_{ij}^{to})^2} \tag{3.16}$$

Wherein P_{ij}^{from}, Q_{ij}^{from}, P_{ij}^{to} and Q_{ij}^{to} are calculated by:

$$P_{ij}^{from} = V_i^2.g_{ij} - V_i.V_j.(g_{ij}.cos\Theta_{ij} + b_{ij}.sin\Theta_{ij}) \tag{3.17}$$

$$Q_{ij}^{from} = -V_i^2.(b_{ij}^{sh} + b_{ij}) - V_i.V_j.(g_{ij}.sin\Theta_{ij} - b_{ij}.cos\Theta_{ij}) \tag{3.18}$$

$$P_{ij}^{to} = V_j^2.g_{ij} - V_i.V_j.(g_{ij}.cos\Theta_{ij} + b_{ij}.sin\Theta_{ij}) \tag{3.19}$$

$$Q_{ij}^{to} = -V_j^2.(b_{ij}^{sh} + b_{ij}) + V_i.V_j.(g_{ij}.sin\Theta_{ij} + b_{ij}.cos\Theta_{ij}) \tag{3.20}$$

3.2.2 DC-OPF model

DC models are approximate models of the AC formulation which consider the same parameters as before, but taking into account also the following assumptions:

- Branch resistances are negligible regarding the corresponding reactances (lossless model), and therefore:

$$g_{ij} \approx 0 \tag{3.21}$$

$$b_{ij} \approx -\frac{1}{x_{ij}} \tag{3.22}$$

- Bus voltages magnitudes are near to the nominal value (1.00 pu);
- Reactive power flows are not considered;

- Voltage angle differences between nodes are small, thus:

$$\theta_{ij} \approx 0 \rightarrow \begin{cases} cos\theta_{ij} = 1 \\ sen\theta_{ij} \approx \theta_{ij} \end{cases} \tag{3.23}$$

Taking into account these assumptions, the active power flows are obtained as linear functions of the voltage angles. Thus, Equation (3.16) and (3.18) are approximated by Eq. (3.24):

$$P_{ij}^{from} = P_{ij}^{to} = \frac{\theta_i - \theta_j}{x_{ij}} \tag{3.24}$$

A major problem regarding DC based approaches is that they do not incorporate losses. This problem can be overcome by an iterative process adequately addressed in (Da Rocha and Saraiva, 2013) as described below:
1. Solve the DC model;
2. Compute voltage phases;
3. Estimate active losses in branch i-j using the equation (3.25) that results from the full AC branch loss expression considering the assumptions inherent to the DC model (namely voltages at 1.00 pu):

$$LOSS_{ij} = 2.g_{ij}.(1 - cos\Theta_{ij}) \tag{3.25}$$

4. Add half of the losses in branch i-j to the original loads in nodes i and j. Update the DC model with these changes and return to step 1 or stop the process if the absolute value difference of voltage phases in all nodes is smaller than a specified threshold.

It is important to note that the DC model has been widely used instead of the AC model in TEP formulations due to the large computational effort that the latter requires. However, in recent years computer processors experienced an extremely rapid technological advance, resulting in core and clocks ever more powerful, which in turn dramatically decreased the time to perform a given task.

3.3 Techniques to solve large scale TEP problems

TEP is a problem that has non-linear and non-convex nature that is usually associated to a large search space very often mentioned as related to a *combinatorial explosion* of the investment options, which means that there are a large number of combinations associated to different sets of investment alternatives for a predefined TEP problem. Unfortunately, the vast majority of these combinations are unfeasible, that is, they do not meet all the security constraints imposed by the planner. In addition, usually there is a reduced number of feasible solutions and in general most of them are related to local optimum. Thus, solving the TEP problem is a very hard challenging task and, in recent years, the TEP approaches were associated to two main paths:

- Relax the problem until the global optimum solution is mathematically possible;

- Approximate iteratively the solution towards the optimum not using a relaxed formulation but the real complete one, instead.

The first approach was widely used in the literature through the relaxed approaches of the DC-OPF model, as for example the transportation model, described in (Mendonça et al., 2016). However, there is no guarantee that the optimal solution found for the relaxed problem corresponds to a feasible solution to the real complete problem. On the other hand, in the second approach, the optimality of the identified solution is not guaranteed, despite it is its feasibility. This is a current and extremely important issue for TEP problem solution approaches, mainly due to the time required to solve it. In the next subsections the main approaches used to make TEP problems computationally scalable are briefly described.

3.3.1 Methods to reduce the search space

Reducing the search space, without eliminating optimal solutions or equipments integrating optimal solutions, can be a good direction to solve TEP problems. In fact, the literature describes several approaches that reduce the search space finding optimal and sub-optimal solutions. The size of the search space can be estimated depending on the approach that is used to solve the TEP problem, that is, static or dynamic. Equations (3.26) and (3.27) present the size of the search space for static and dynamic TEP formulations, respectively, in which N_{proj} represents the number of different possible projects that can be selected to compose an investment alternative. In (3.27) p represents the number of periods in the planning horizon in case a dynamic model is used.

$$SSS^{static} \approx 10^{log2^{N_{proj}}} \tag{3.26}$$

$$SSS^{dynamic} \approx 10^{log(p+1)^{N_{proj}}} \tag{3.27}$$

According to these equations, the well-known IEEE 118 bus test system has the search space that includes about 10^{112} investment alternatives when the TEP is conducted in a static way and considering all branches as possible expansion routes and a maximum of 2 insertions per branch. This is a huge number, if, for example, we wanted to perform the TEP without relaxations we would only be able to guarantee a global optimal solution by a complete enumeration, which means that all the search space should be analysed. However, if we had a computer capable of evaluating 1000 investment alternatives per second (solving the associated OPF problems) when solving TEP under the static approach, we would have covered only less than 1% of the search space in 15 billion years from now, which makes the enumeration process impractical for this kind of problems. That is why tools that are able to explore the search space in an intelligent way, namely the metaheuristics, are being increasingly used to solve TEP problems.

In fact, it is currently common to use metaheuristics associated with a space reduction process conducted by Constructive Heuristic Algorithms, known as CHAs. These hybrid tools are presenting good results regarding both the computational effort and the quality of the solutions achieved. As examples of the application of this type of hybrid approaches:

- (De Mendonça et al., 2014) employs the Garver CHA in order to reduce the search space without losing relevant solutions, and a PSO to build the final solution plan from the reduced search space;
- (Gomes and Saraiva, 2015) uses the Garver and the Least Effort CHAs to reduce the search space and a PSO was applied to refine the solution plan;
- (de Mendonça et al., 2016) uses a new heuristic based on a portfolio of indices to reduce the search space and a PSO to find the final solution in the reduced search space.

In either case, the general structure of this hybrid approach is illustrated in Fig. 3.1.

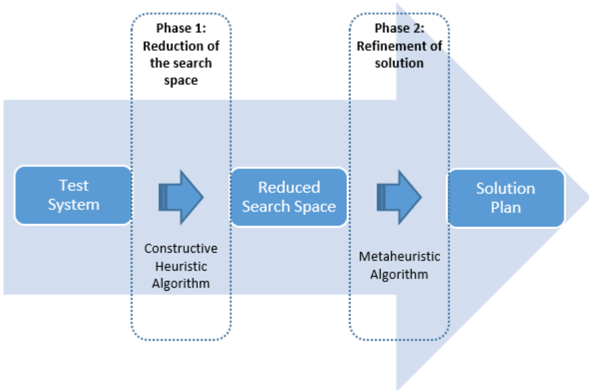

Figure 3.1: TEP handled by a hybrid structure.

3.3.2 Parallel computing

In recent years, technological advances in computer processing power has been providing access to multi-core computers,which in turn accelerates some large-scale procedures that request huge computational effort as the TEP problem. So, with the parallel computing approach, the server supports operations in a completely independent way of each other without requiring any type of information between these operations, that is, the different existing cores are put to drive the independent pieces of the problem simultaneously, increasing the computational effort even more, but decreasing the computational time for the final solution plan.

Fig. 3.2 and Fig. 3.3 show the behavior of the computer cores when the simulations to be detailed at the end of Chapter 3 were conducted in Matlab environment without parallel computing and if this approach is used, respectively.

According to Fig. 3.2 and Fig. 3.3, when the TEP problem is solved using the parallel computing approach, the required CPU usage and the memory are much larger than when this approach is not used. As a result of this more intensive use of CPU and memory and according to (Gomes and Saraiva, 2017a), the parallel implementation of the TEP optimization problem is able to reduce the computation time by about 70%.

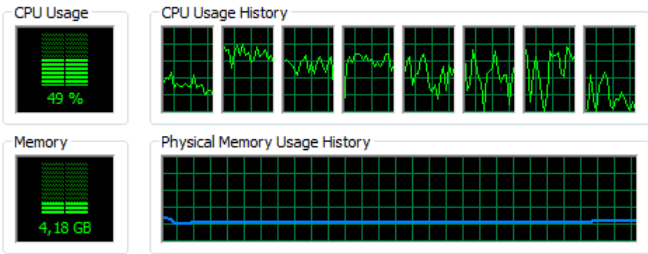

Figure 3.2: Without parallel computing - CPU behavior.

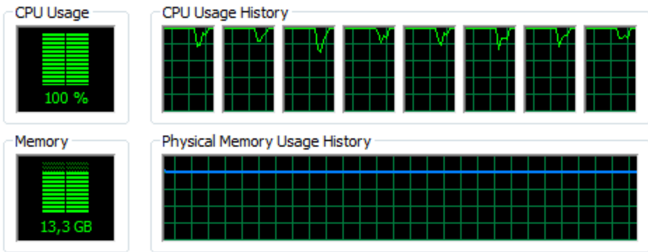

Figure 3.3: With parallel computing - CPU behavior.

3.4 Constructive Heuristic Algorithm (CHA)

A Constructive Heuristic Algorithm (CHA) performs the TEP expansion process step by step. In this type of techniques it is performed a sensitivity analysis using a function responsible for assessing the system performance and the expansion cost with respect to the addition of a transmission line. Therefore, in each step a circuit is selected taking into account a sensitive indicator that typically has the following characteristics:

- Be able to identify the most attractive paths to add transmission lines;
- Be a local character indicator;
- It is not guaranteed the convergence to the global optimum.

Besides, the CHAs used in TEP problems usually works as follows. First of all, it is solved an AC or DC-OPF considering the base case system and the forecasted electricity demand (usually the peak load). If the solution of the optimal dispatch indicates that there is at least one violation of the security constraints as non zero power not supplied, overload of network equipments (transmission lines and transformers) or if the system is not able to safely operate under the N-1 contingency criterion, for instance, then a new equipment should be inserted on the grid in order to overcome the above problems.

The new addition follows a predefined sensitivity indicator (least load shedding, least congestion on the lines, etc). After selecting this equipment, the system is update with the new topology and the optimal dispatch is solved again. The additions continue to be made until the system operates properly while supplying the forecasted load. Fig. 3.4 shows a block diagram illustrating the CHA process.

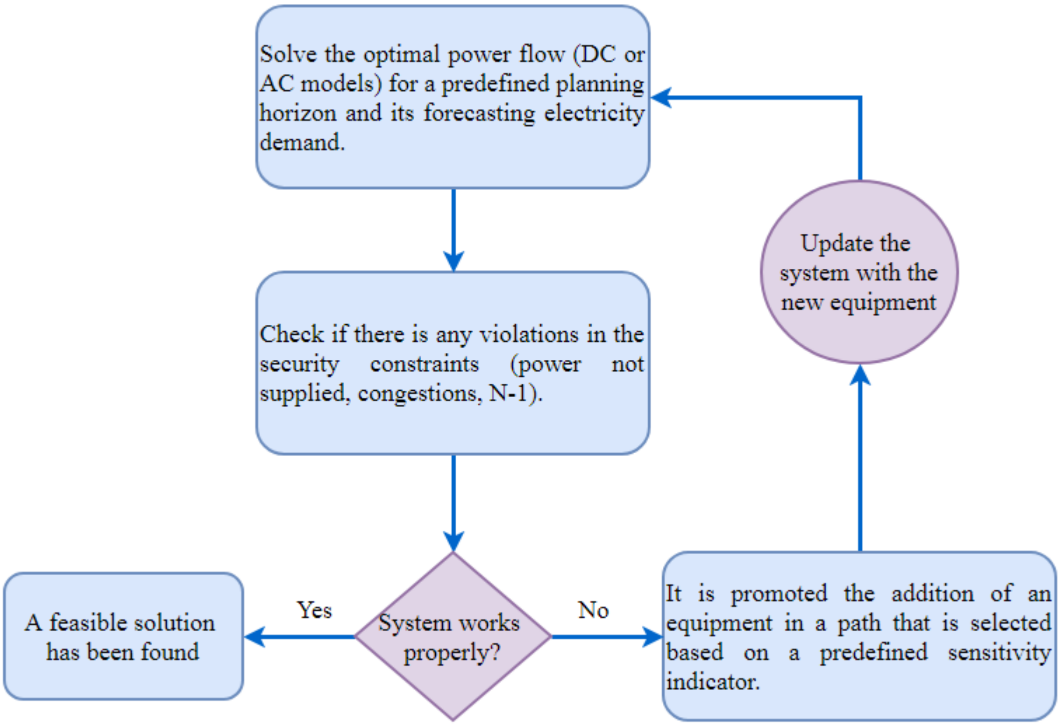

Figure 3.4: Main blocks of a CHA algorithm.

CHAs are tools that were designed to solve the TEP problem from the 70s when the computer processing revolution had not yet occurred and a simpler and reasonable solution approach was necessary. They were widely used in the literature between the 80s and 90s. The CHAs were developed using relaxed approaches of the DC model, but they can also be used considering the AC-OPF based models.

From the 2000s, this technique began to be used in a hybrid way together with metaheuristics (particle swarm optimization, genetic algorithms, etc). In these cases, the CHAs were used in TEP and its solution was used as input (the initial solution) in metaheuristic module that would then provide its eventual refinement.

In the next section, the main CHAs used to solve TEP problems as well as their respective DC formulations and sensitivity indicator are briefly presented.

3.4.1 Garver CHA

This CHA was proposed to solve the TEP problem by (Garver, 1970) and uses a modified version of the DC model that takes into account only the first Kirchhoff law. Therefore, the Garver CHA relaxes even more the DC Model because it accepts continuous values to n_{ij}, variable representing the number of additions in route i-j, and the capacity of the transmission lines are ignored during the dispatch.

It is clear that a solution with fractional transmission lines is not technically feasible and can't be accepted as a global solution to the TEP problem. However, it can be used as a strategy in an attempt to find a good initial value to these integer variables through the sensitivity indicator (SI) presented in Equation (3.28) in which n_{ij} is the number of circuits to be built from i to j and f_{ij}^{max} is the maximum active power flow allowed in the branch connecting i to j.

$$SI_{ij}^{garver} = n_{ij}.f_{ij}^{max} \tag{3.28}$$

Thus, the Garver CHA consists of using the corresponding linear programming problem only as a strategy to find a good solution for planning purposes and it includes the steps displayed in Fig. 3.4 with the SI presented in Equation (3.28). The main problems with this approach are:

- Some added equipments may become irrelevant with the later addition of other more important ones. This problem can be addressed by adding an extra step in which irrelevant equipments are detected and removed;
- The sensitivity indicator may become inefficient when (3.28) has a very small output, because it represents where the equipment will be inserted on the grid. This problem can be minimized by choosing a minimum threshold for new additions.

3.4.2 Least Effort CHA

The Least Effort CHA was proposed by (Monticelli et al., 1982) and uses the DC Model to solve the TEP problem. In one hand, the least Effort CHA relaxes the DC Model as the Garver CHA because it also accepts continuous solutions to the n_{ij} variables and the capacity of the transmission lines are ignored during the dispatch. On the other hand, the Least Effort CHA represents in a more adequate way the problem once it considers both Kirchhoff laws. The relaxation in the n_{ij} variables is used as an attempt to find a good solution to these originally integer variables through the sensitivity criterion given by Equation (3.29).

$$SI_{ij}^{LE} = -\frac{1}{2}.(\theta_i - \theta_j)^2.b_{ij} \tag{3.29}$$

Equation (3.29) allows identifying the most adequate equipment to overcome any overloaded one, that is, at each iteration the most overloaded equipment is identified and a new equipment is inserted on the grid in order to decrease the mentioned overload. The main problems with this approach are (Mendonça et al., 2016):

- If the system under analyses includes isolated buses, the DC model presents convergence problems;
- To obtain the index presented in Equation (3.29) it is necessary to obtain the voltage angles in all buses.

These problems were overcome by overlapping a fictitious network to the base network topology. In this fictitious network the equipments are configured to have low susceptance values when compared with the susceptances of the candidate equipments. Therefore, this methodology connects the isolated buses and the DC model can then be run without difficulty.

3.4.3 Least Load Shedding CHA

The Least Load Shedding CHA was proposed by (Pereira and Pinto, 1985) and uses a modified DC Model by including fictitious generators with costs larger than the ones of real generators. However, differently from the previous two CHAs, the capacity of the transmission lines is considered.

In this way, the fictitious generators represent the power not supplied, and the CHA looks at each iteration for new equipments that are able to reduce it. The insertion of new equipments on the grid follows the sensitivity indicator presented in Equation (3.30). In this formulation π is the Lagrange multiplier of the real power balance equation for node in (3.2) which now also considers the fictitious generators.

The Lest Load Shedding CHA present the same problems that Garver and the Least Effort CHAs with convergence for isolated systems.

$$SI_{ij}^{LLS} = -(\theta_i - \theta_j).(\pi_i - \pi_j) \tag{3.30}$$

The sensitivity indicator presented in Equation (3.30) allows identifying the most appropriate equipment to be inserted in the network in order to reduce the load shedding in the system.

3.4.4 Sigmoid CHA

The Sigmoid CHA was proposed by (de Oliveira et al., 2005) in 2005 and uses the DC model and the primal-dual interior points methodology as solution technique. The binary variable PE associated to investment decisions in route i-j is given by Equation (3.31) in which k is the argument of the sigmoid function.

$$PE_{ij} = \frac{e^k - 1}{e^k + 1} \tag{3.31}$$

The sensitivity indicator is based on the Garver SI and it is given by Equation (3.32).

$$SI_{ij}^{S} = -PE_{ij}.b_{ij}.\theta_{ij} \tag{3.32}$$

The Sigmoid CHA was a great leap compared to the others CHAs since it used a more complete DC model even considering an approximation for the transmission losses. The Sigmoid CHA was able to find optimal and sub-optimal expansion solutions for a Brazilian equivalent transmission system.

3.4.5 Portfolio of Indices CHA

This CHA was proposed by (Mendonça et al., 2016) and the variable expansion decision (EP) is represented by the hyperbolic tangent function. EP is given by Equation

(3.33) in which A is the sigmoid slope.

$$EP_{ij} = \frac{e^{k/A} - 1}{e^{k/A} + 1} \tag{3.33}$$

This CHA also uses the DC-OPF model to represent the operation of the network. Its output is obtained by varying the slope of the mentioned function and also by using a portfolio of sensitivity indicators. This portfolio of sensitivity indices is composed by the main SI available in the literature as SI^{garver}, SI^{LE} and SI^{LLS}.

The Portfolio of Indices CHA was able to find optimal and sub-optimal solutions for the complete Colombian transmission system.

3.5 Bio-inspired algorithms

Complex problems that are difficult to solve using traditional techniques have been addressed for many years by a simple and efficient iterative process where the rule was to save the best solution found so far and look for better solutions in the neighborhood. Thus, when a new and better solution was found, it was updated as well as the new neighborhood to search for new solutions.

However, this deterministic process loses its efficiency drastically in problems that present several local optimum solutions in their search spaces since they did not accept worse solutions in an iteration as an attempt to find better solutions in other neighborhoods, and thus the process can be stuck on local optima.

Thus, in order to overcome this issue, new probabilistic neighborhood search processes were presented to the scientific community, such as simulating annealing. These processes allowed accepting worse solutions (with a low acceptance probability) in order to look for better solutions in other neighborhoods and avoid getting stuck on local optima.

Nevertheless, in complex problems that present the phenomenon of combinatorial explosion together with non-convex solution spaces, these processes could take impractical computational times. In addition, given the huge size of the search space, the solution could still be stuck on local optima, although this is less likely than in deterministic processes.

Thus, optimization techniques that consider a set of solutions and explore the search space in the respective neighborhoods, using a pre-defined rule, started to be used to solve these problems. These techniques correspond to the **population-based evolutionary computation**.

These methods became very spread in the last years mainly due to the evolution of computer processing. Many of the population-based evolutionary computation methods are metaheuristics that use a rule to explore the search space based on specific behaviors. Bio-inspired tools extract this specific behavior from nature, such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO) and Evolutionary Particle Swarm Optimization (EPSO) that will be described in the next subsections.

Before exploring these algorithms and their peculiarities, it is necessary to know important concepts of **encoding**. . It is the first decision to be considered, that is, how the problem will be mapped into a finite string of symbols. In this Doctoral Thesis, a solution is identified as an expansion plan which means that it corresponds to list of candidate equipments (transmission lines, transformers, cables, etc) to be inserted on the grid and that typically are a subset of longer list of possible network additions.

In GAs, this solutions is called *individual* and in PSO and EPSO it is called a *particle*. When addressing the static approach of the TEP problem it corresponds to a binary vector representing the addition (ones) or not (zeros) for the list of equipments. A set of individuals and particles is called a *population* or a *swarm*, respectively. Fig. 3.5 presents an illustration of these concepts.

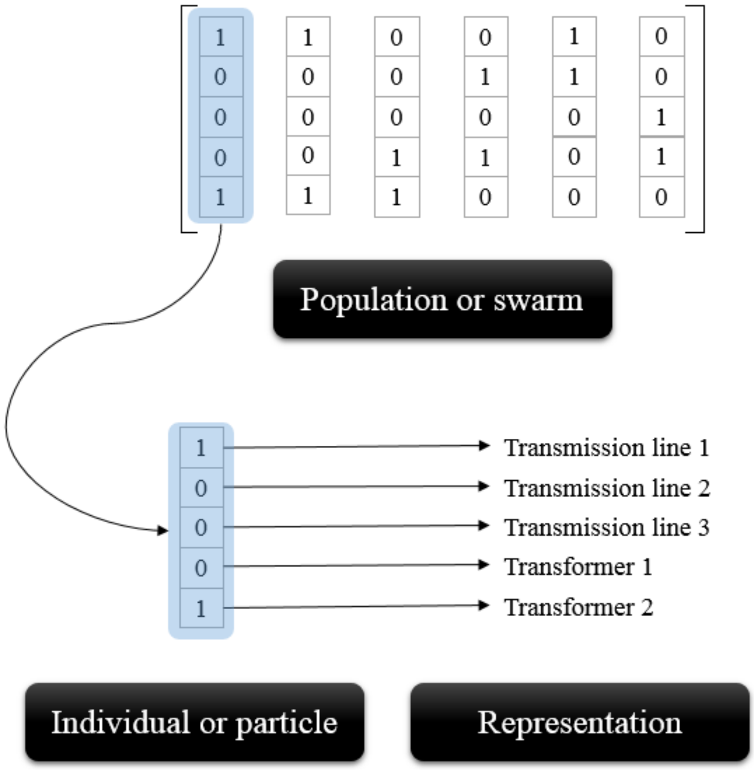

Figure 3.5: Encoding static TEP solutions in GA, PSO and EPSO metaheuristics.

In dynamic TEP approaches, the solutions (individuals or particles) are represented by a vector containing as many positions as the equipments in the complete list of possible additions. Therefore, each position is related to a candidate equipment and this position contains a value from 0 to the number of years in the planning horizon. The 0 indicates that this equipment is not part of this solution (is not added in any year of the horizon) while a value from 1 to the number of years in the horizon indicates the addition year. This coding strategy is illustrated in Fig. 3.6.

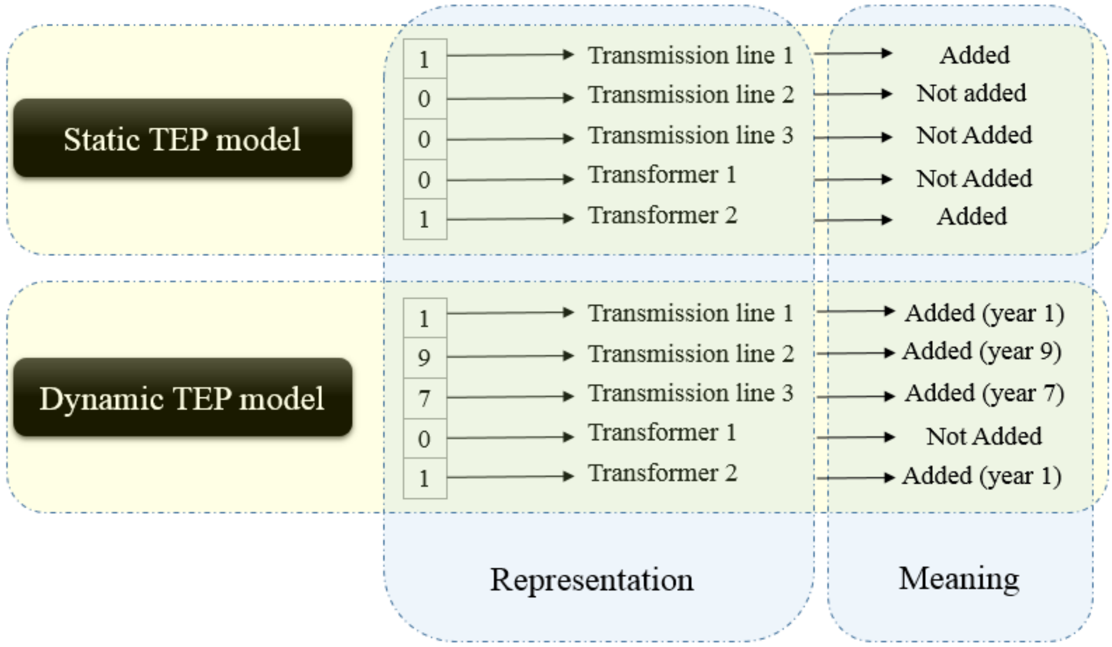

Figure 3.6: Representation and meaning of encoded TEP solutions.

3.5.1 Genetic algorithm

Genetic algorithms are tools inspired on the behavior of natural selection of species. In this type of tool, the individuals (candidate solutions) of a population are likely to survive, that is, to be part of the next generation depending on its fitness function, which in turn measures the quality of this solution and that has a clear relation to the objective function of traditional optimization problems.

In genetic algorithms, the *genes* or *chromosomes* are represented by the values within the vectors as in Fig. 3.6. Genetic algorithms have different types of implementation available in literature. However, the approach adopted in this research uses the blocks and genetic operators identified in Fig. 3.7 and that are described in the next paragraphs.

i **Initial Population** - Generally, the initial population is chosen randomly in which each gene is within the possible values considering the search space. This means it can take a value from zero to the planning horizon in the dynamic approaches and zero or one for the static approaches;

ii **Evaluation** - The population is evaluated taking into account the fitness function defined for the problem. In TEP problems, the fitness function can be associated to investment costs, operation costs, reliability costs, etc;

iii **Crossover** - In the crossover block two different individual are identified and their genes are mixed in order to create new individuals, which are called *offsprings*. It is a controversial operation because it can split important information that can be present in the original individuals. Traditional GA uses one point to make the split, but this operation can also be done with more than one crossover point, as shown in Fig. 3.8;

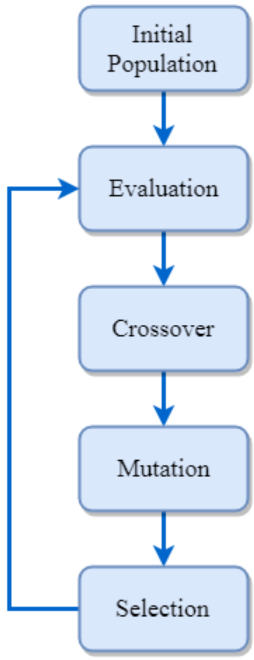

Figure 3.7: Main blocks of a GA.

iv **Mutation** - In this operation block, the offsprings have some genes changed. Mutation is an important operation because it can contribute to reintroduce lost genes and can improve the diversity of the population, even when the process is close to convergence. An example of mutation operation is presented in Fig. 3.8;

v **Selection** - The last block of a GA is the selection and this operation acts over the set of original individuals and offsprings. It is responsible for the selection of the new individuals that will be part of the next generation. There are many different ways to perform this operation as:

- Tournament selection: Two individuals (original ones or offsprings) are randomly chosen and the individual with the best fitness (smaller for minimization problems and larger for maximization problems) is selected for the next generation;

- Elitist selection: The original individuals and the offsprings are ranked and the individuals with the best fitness function are selected for the next generation.

The stop criterion is, generally, set in terms of running a maximum predefined number of generations or checking if the best solution remains unchanged for a predefined number of iterations.

There are, however, some problems that can happen when using Genetic Algorithms (Lee and El-Sharkawi, 2008), as **premature convergence** and the **slow finishing**. The first problem is related with some genes from some individuals that may rapidly dominate the population, and therefore the final solution converges towards a local optimum. On the other hand, the latter problem is the opposite, which means that after running generations the process continues improving the current population sometimes by small amounts.

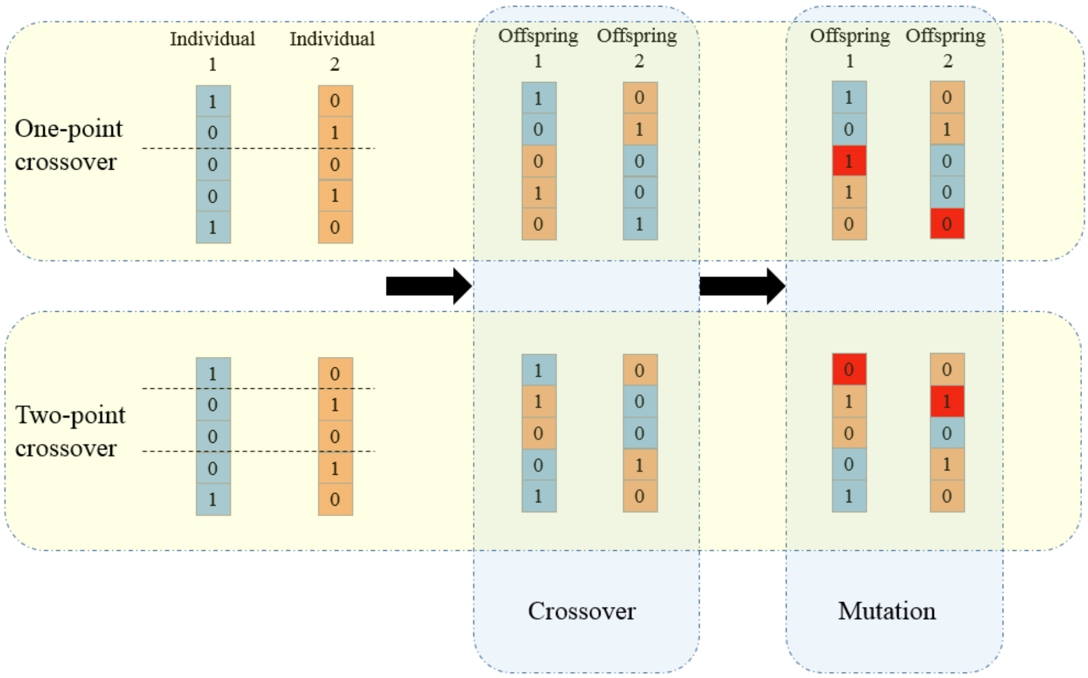

Figure 3.8: An example of crossover and mutation in GA.

3.5.2 Particle swarm optimization

PSO is a swarm intelligent technique and a stochastic optimization algorithm based on social simulation models. The development of PSO was based on concepts which govern socially organized populations in nature, such as bird flocks, fish schools and animal herds (Eberhart et al., 2001). This technique employs a set of particles (candidate solutions) that move in the search space. The best position reached by each particle is maintained, and then communicated to all particles in the swarm. Each of these particles is characterized by a value that measures the suitability of the particle as a solution to the problem. Each particle evolves along the solution algorithm using a velocity vector that defines the direction of its movement. The swarm is successful over time because the position of each particle is updated, taking into account the best position of the particle in the past generations and the best position of all particles in the swarm. The velocity of each particle is given by Equation (3.34) and the position is obtained by Equation (3.35).

$$\nu_i^{it+1} = c_1.\nu_i^{it} + c_2.rand_1.(p_{best} - \chi_i^{it}) + c_3.rand_2.(g_{best} - \chi_i^{it}) \tag{3.34}$$

$$\chi_i^{it+1} = \chi_i^{it} + \nu_i^{it+1} \tag{3.35}$$

In expression (3.34) ν is the velocity of particle *i* at iteration *it*, c_1 is given by a weighting function, c_2 and c_3 are weighting coefficients, rand is a random number in [0,1], p_{best} is the best position find so far by the particle, χ is the position of particle *i* at iteration *it* and g_{best} is the best particle in the entire swarm. This movement rule is illustrated in Fig. 3.9.

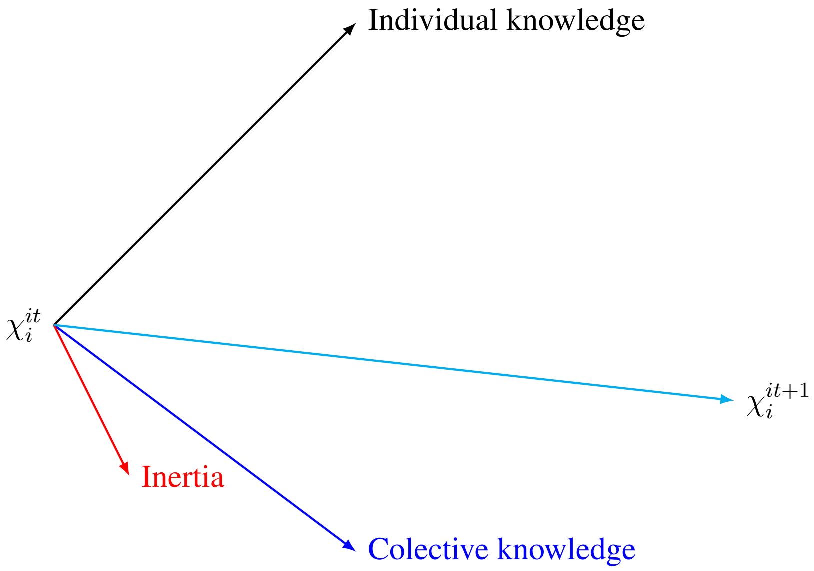

Figure 3.9: Particle movement rule in typical PSO algorithms.

The stopping criterion is usually given by a function that establishes a maximum or a minimum range for the evolution of PSO parameters or a maximum number of iterations.

Regarding Equation (3.34) the first term $(c_1.\nu_i^{it})$ refers to the moment of inertia of the particle.

The second term $(c_2.rand_1.(p_{best} - \chi_i^{it}))$ refers to the "cognitive" part, which represents the individual knowledge of the particle acquired over the search process.

The third term $(c_3.rand_2.(g_{best} - \chi_i^{it}))$ refers to the "social" part, which represents the collaboration between the particles, i.e, the collective knowledge gained by the swarm throughout the search process.

The second and third terms are weighted by two coefficients (c_2 and c_3) that represent the weighting of the individual and collective components respectively and influence each particle towards the new solution. The first term is weighted by a function (c_1), called inertial weighting function presented by Equation (3.36), that induces the particle to move in a direction based on the move of the previous iteration. In this Equation c_{1max} is the initial weight, c_{1min} is the final weight and it_{max} is the maximum iteration number.

Larger values of the weighting function facilitate a global search while smaller values tend to represent a local one. Results provided in the literature mention that it is better to adjust the weighting function for a larger value at the beginning of the search process, promoting a more comprehensive search, and gradually, throughout the iterative process, reduce it to refine the search (Mendonca et al., 2013).

$$c_1 = c_{1max} - \frac{c_{1max} - c_{1min}}{it_{max}}.it \tag{3.36}$$

There are some issues regarding optimization problems solved by the PSO. An important issue that is commonly raised is related to the c_1 function, which has parameters that must be defined by the user and requires, necessarily, some previous knowledge about the problem to tune it. Furthermore, the random factors driven by *rand* are not sensitive to the evolution of the process.

3.5.3 Evolutionary particle swarm optimization

EPSO is a powerful tool that combines concepts of evolutionary computation and multi agent population taking advantage of the standard blocks that are typical in Genetic Algorithms and Particle Swarm Optimization. In fact, in (Miranda and Fonseca, 2002) EPSO is reported to be able to overcome the problems mentioned about the GAs and the PSO. Namely, EPSO is a self-adaptive process (PSO issue) that avoids premature convergence and slow finishing (GA issues).

This tool is able to combine the best features of these two groups of techniques and so it typically shows an excellent performance in solving complex problems such as the one addressed in this Doctoral Thesis.

The EPSO algorithm is based on the evolution of a set of particles, each of them representing candidate solutions for the problem. Along the process, the particles evolve according to a fitness function and continue to improve in each iteration until the process reaches a pre-established stopping criterion. At this point, the best solution of the last population is provided to the user. Fig. 3.10 details the main blocks of the EPSO algorithm that will also be described in the next paragraphs.

i **Initial Population** - The initial population is chosen randomly similarly to genetic algorithm;

ii **Replication** - Each population is cloned *r* times in order to create new populations that will be mutated in the next block;

iii **Mutation** - The weights and the best particle found until now (g_{best}) for the populations are mutated using Equations (3.37) and (3.38) in which the symbol * denotes the mutation operator. This process increases the diversity of the individuals under analysis;

$$w_{ij}^{*it+1} = 0,5.rand - \frac{1}{1+e^{-w_{ij}^{*it}}} \tag{3.37}$$

$$g_{best}^{*} = gbest + round(2.w_{i4}^{*it+1} - 1) \tag{3.38}$$

iv **Recombination** - Offsprings are created based on the PSO movement rule using Equations (3.39) and (3.40) for each cloned population;

$$\nu_i^{it+1} = w_{i1}^{*it+1}.\nu_i^{it} + w_{i2}^{*it+1}.(p_{best} - \chi_i^{it}) + w_{i3}^{*it+1}.rand_2.(g_{best}^{*} - \chi_i^{it}).\Psi \tag{3.39}$$

$$\chi_i^{it+1} = \chi_i^{it} + \nu_i^{it+1} \tag{3.40}$$

v **Evaluation** - This process is identical from the GAs;

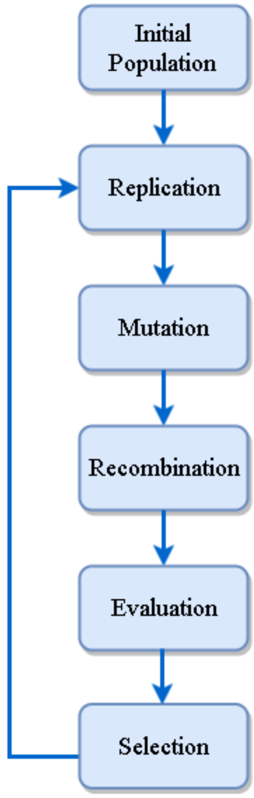

Figure 3.10: Main blocks of the EPSO algorithm.

vi **Selection** - This process is identical from the GAs;

The term Ψ in Equation (3.39) is the communication factor, introduced in (Miranda et al., 2008). This factor induces a stochastic star topology among the particles in the swarm communication. This communication topology is presented in Fig. 3.11 in which the star communication topology is represented on the left side and the stochastic star topology on the right side. The impact of the stochastic communication among the particles is that it can improve the local search and avoid premature convergence.

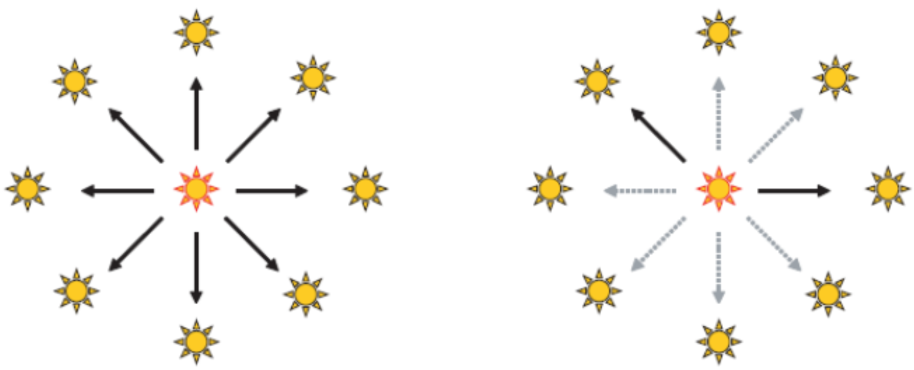

Figure 3.11: EPSO communication topology (Source (Miranda et al., 2008)).

3.6 Proposed security CHA

This section proposes a constructive heuristic algorithm for TEP problems that uses the AC-OPF model and considers the N-1 contingency criterion which typically are time consuming approaches. The algorithm of the developed security CHA is presented in Fig. 3.12 and works as described below.

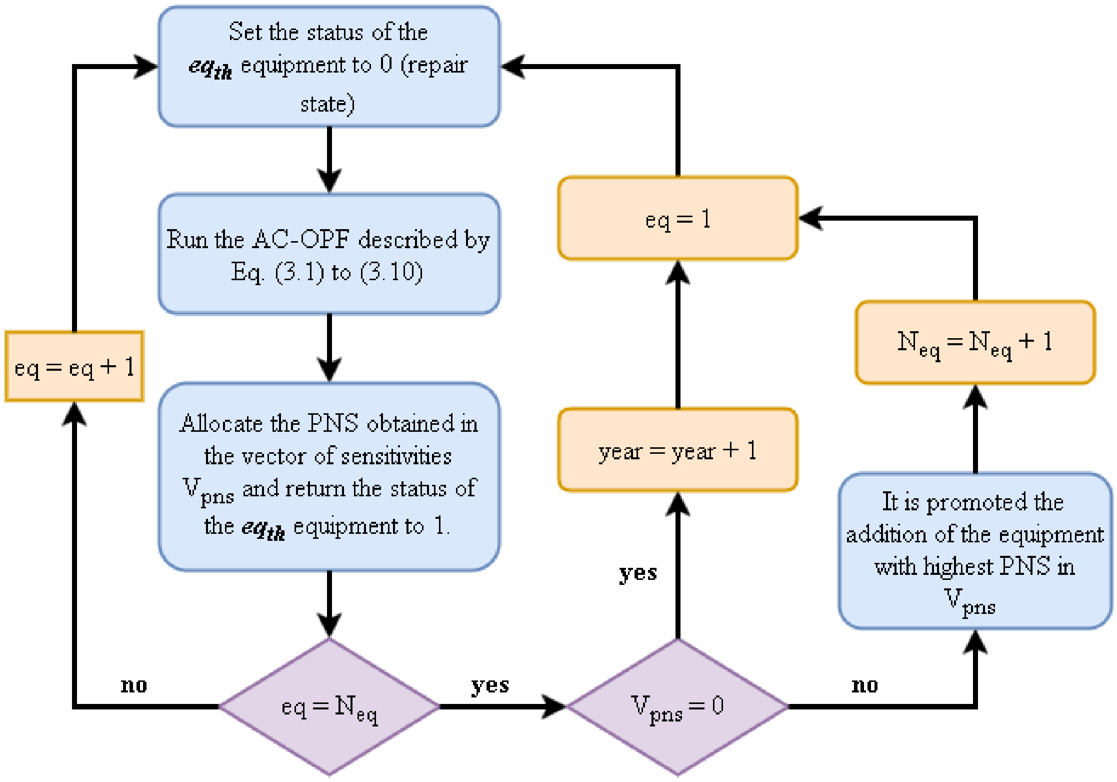

Figure 3.12: Algorithm of the proposed security CHA.

In the first place, we consider that the state of the equipment eq in the bulk system can be switched to 1 representing normal operation and 0 representing a fault in this equipment that needs to be repaired. We are also considering that the system has N_{eq} equipments in the starting year of the planning exercise and that all equipments are initially in the normal operation state, that is, its state is equal to 1. Let us also admit that the new equipments that can be inserted in the system are equal to the existing ones, that is, new equipments will be included if necessary in parallel with the existing ones. Finally, we consider the sensitivity vector V_{pns} that stores the value of PNS that is obtained from running the AC OPF problem admitting that one equipment at a time is out of service. In the beginning of this procedure, this vector has N_{eq} positions and this value will be increased as the algorithm evolves and new equipments are inserted in the network. The security CHA operates iteratively according to the steps described below:

i Change the state of the equipment eq to 0 and solve the AC-OPF described in Subsection 3.2.1 by Eq. (3.1) to Eq. (3.10);

ii Allocate the PNS obtained from this calculation into the sensitivity vector V_{pns} at the eq_{th} position and return the equipment state of eq to 1;

iii Increment eq by one unit and return to step i until the condition $eq = N_{eq}$ is reached. At this moment proceed to step iv;

iv Check if the sensitivity vector V_{pns} has any non-zero value of PNS. If so, add the equipment associated with the highest value of PNS in V_{pns}, update the system with this addition, increment N_{eq} by one unit, set eq equal to one and return to step i. If not, that is, if there are just zero values in V_{pns}, increment year by one unit and set $eq = 1$ and return to step i. The process ends when year is equal to the planning horizon ($year = np$).

Thus, at the end of this process it is obtained a modified system considering the list of equipments together with the insertion year. With these additions the system is able to guarantee a safe operation considering the N-1 criterion. The mentioned list of added equipments can now be used as a list of candidate equipments in a more powerful tool (such as a metaheuristic). The vector indicating the year of entry of each candidate equipment can be used to build one of the initial solutions of the swarm or population to improve the performance of the search for optimal solutions.

3.7 Numerical simulations

In this section we present the results of the simulations related to the contents of this chapter as a way to highlight the performance of the proposed tools. We conduct the TEP problems in different ways considering four simulation cases as follows:

- **Case 1** - TEP problem is solved using the AC-OPF model described in Subsection 3.2.1 by Eq. (3.1) to (3.10). TEP is solved ten times under the same considerations by the Genetic Algorithm, Particle Swarm Optimization and by the Evolutionary Particle Swarm Optimization in order to get a global view on the behavior of each tool;
- **Case 2** - This case is similar to Case 1, but using the DC-OPF model described in Subsection 3.2.2;
- **Case 3** - In this simulation the solution plans obtained by the Case 1 and 2 are compared. Furthermore, the DC solutions are tested in the system using the AC-OPF equations in order to verify if these DC results are trustworthy or if they provide operational violations when considering the AC equations and constraints;
- **Case 4** - The proposed security CHA is tested to solve the TEP problem considering the N-1 contingency criterion and using the AC-OPF model.

All simulations were performed using a modified version of the IEEE 118 Bus test system. The system has 118 buses, 54 generators and 186 branches, the installed capacity is 9966 MW and the peak demand is 6363 MW in the starting year of the planning exercise.

Regarding the planning parameters, all simulations used an annual demand growth of 3%, the size of the population/swarm is 20 individuals/particles, the replication parameter

(r) of the EPSO is equal to 3 and the stopping criterion for all tools corresponds to run 20 consecutive iterations with the same best fitness function. The planning horizon is set at 10 years and all simulations were done in an Intel i7 with 16 GB RAM and clocked at 3.4 GHz, and using parallel computing to reduce the computation time.

The simulations performed in all case studies used the minimization of investment cost in new equipments as the objective function. However, only in the simulations of Case 4, the single contingency criterion was considered.

Therefore, the objective function of Case 1, Case 2 and Case 3 (OF1,2,3) is given by Eq. (3.41), $C_{inv,p}$ is the investment cost in period p, β_1 is the penalization factor for power not supplied in period p (PNSp) and κ_p is the present worth coefficient given by Eq. (3.43).

The objective function of the Case 4 (OF_4) is given by Eq. (3.42) in which β_2 is the single contingency penalization factor that penalizes candidate solutions that have non-zero PNS for any N-1 contingency. In this case, N_{cont} corresponds in each period p to the number of contingencies regarding which it was obtained a non zero value for PNS.

$$OF_{1,2,3} = \sum_{p=1}^{np} (C_{inv,p} + \beta_1.PNS_p).\kappa_p \tag{3.41}$$

$$OF_4 = \sum_{p=1}^{np} (C_{inv,p} + \beta_1.PNS_p + \beta_2.N_{cont,p}).\kappa_p \tag{3.42}$$

$$\kappa_p = \frac{1}{(1+d)^p} \tag{3.43}$$

- **Case 1 - Results**

TEP using the AC-OPF models was solved using GA, PSO and EPSO in order to minimize the investment costs according to Eq. (3.41). The simulations were repeated 10 times in order to better acquire the behavior of these tools in solving the problem. The best solution found by these tools corresponds to the insertion of a 138 kV line connecting buses 77 and 78 in the fourth year, this solution has the present value of 10.20 million USD. The behavior of each mentioned tool is displayed in Fig. 3.13 in which we can observe that the EPSO has the smaller interquartile range and that the PSO presents the worst outlier represented by +.

Table 3.1 provides additional information about these simulations. According to this table, GA was able to find the best global solution in 10% of the simulations, PSO in 70% and EPSO in 70%. EPSO behaved better than the other tools by providing cheaper average solutions but it requires a higher computational time.

- **Case 2 - Results**

In this case, TEP using the DC-OPF model was solved using GA, PSO and EPSO in order to minimize the investment costs according to Eq. (3.41). As in Case 1, the simulations were repeated 10 times in order to get insight about the behavior of these tools in solving the problem. The best solution found by these tools corresponds to the insertion

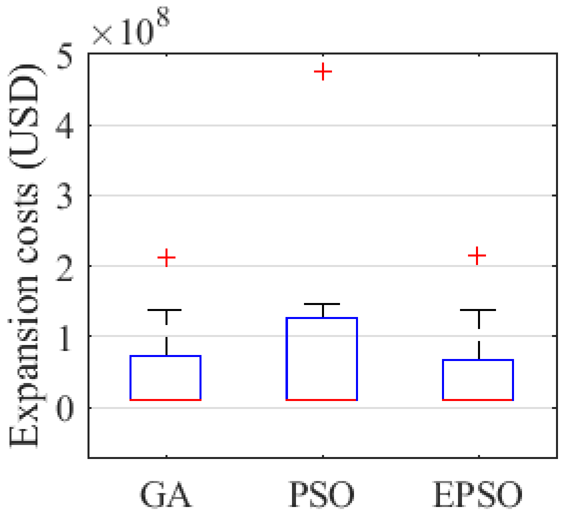

Figure 3.13: Behavior of GA, PSO and EPSO in solving the AC TEP problem.

Table 3.1: TEP solutions by tool - Case 1

	Average solution (mi USD)	Found the best solution	Average computational time (h)
GA	50.08	10%	1.06
PSO	81.96	70%	0.77
EPSO	48.82	70%	1.09

of a 138 kV line connecting buses 77 and 78, as in Case 1, but now the insertion occurs in the seventh year. As the investment was postponed regarding Case 1, this solution is cheaper and has the present value of 8.81 million USD. The behavior of each mentioned tool is displayed in Fig. 3.14 in which we can recognize that the GA has the smaller interquartile range and that the PSO and EPSO behaved quite similarly.

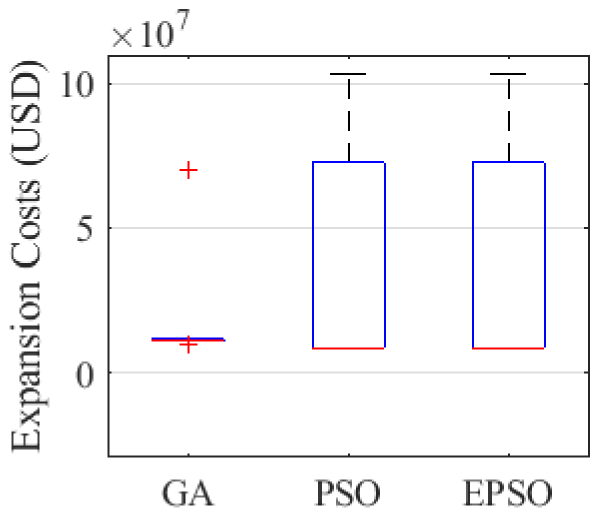

Figure 3.14: Behavior of GA, PSO and EPSO in solving the DC TEP problem.

Table 3.2 provides additional information about the simulations in Case 2. According to this Table, GA was not able to find the best global solution although in 90% of the simulation runs the GA solutions were very close of the best solution. PSO and EPSO tools were able to find the best solution in 70% of the simulations. Although PSO and EPSO presented a better behavior in finding the best solution, they present solutions with larger costs when the optimal one was not obtained, which increases the average cost of both PSO and EPSO.

Table 3.2: TEP solutions by tool - Case 2

	Average solution (mi USD)	Found the best solution	Average computational time (h)
GA	17.10	0%	0.34
PSO	31.42	70%	0.16
EPSO	32.07	70%	0.36

- **Case 3 - Results**

Let us recall that in Case 1 the TEP problem is solved using the AC-OPF, and that the best planning solution has an investment cost of 10.20 million USD. On the other hand, in Case 2 TEP was solved using the DC-OPF, and the best solution that was found has an investment cost of 8.81 million USD. The computational time for solving the TEP using the DC model is much lower than that using the AC OPF model, and this is the main motivation for the wide use of DC-OPF in recent years by the academy and the power industry to solve the TEP problem. Fig. 3.15 shows the comparison between the times used in the simulations of Cases 1 and 2. According to this figure, the computational time required to solve the TEP problem using the DC formulation gets reduced by about 72% regarding the one using the AC OPF formulation..

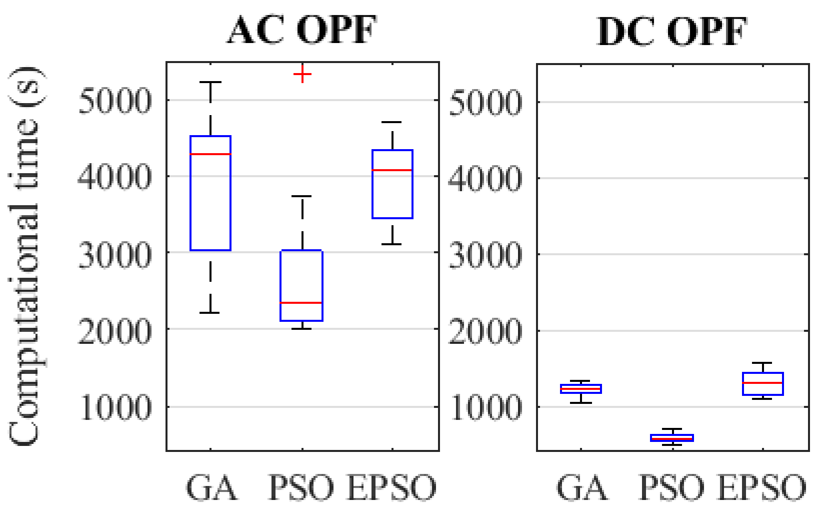

Figure 3.15: Comparison of computational time required in cases 1 and 2.

Therefore, the DC formulation provides cheaper solutions for the TEP problem in a faster way when compared to AC formulations. In order to verify the quality of the expansion plans obtained with the DC model, the corresponding solutions are tested in the real network, that is, using the equations of the AC model. Thus, it is possible to know if these solutions exhibit significant constraint violations when tested using the full AC power flow model. Fig. 3.16 shows the PNS obtained by this analysis by the GA, PSO and EPSO tools. For each of the ten simulations using the GA, the PSO and EPSO tools, this Figure indicates the global value obtained for PNS as the sum of the values obtained for each year of the planning horizon.

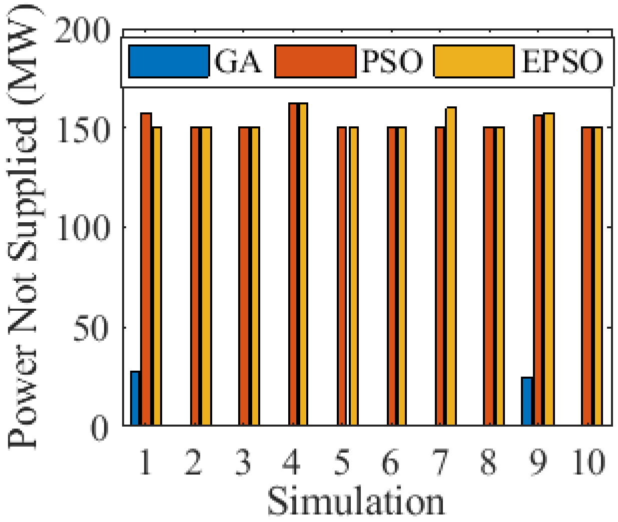

Figure 3.16: Evaluation of the quality of TEP solutions obtained by DC formulations when tested using AC equations.

As can be verified, the solution plans built by the EPSO and PSO tools show non zero PNS values in all simulations when these plans are tested using the AC equations, GA solution plans also present non zero PNS in 20% of the simulations when this test is done. It is important to note that GA was not able to find the best global solution in any simulation with the DC model. Because of that, it presented a lower level of PNS when compared to the PSO and EPSO, which were able to find this global solution in 70% of the simulations.

- **Case 4 - Results**

The CHA proposed in Section 3.6 was applied with the purpose of reducing the search space of the TEP problem and to initialize in a better way the population of the search procedure. This means that prior to the solution of the TEP problem, it was used the proposed CHA over a list of 558 candidate equipments composed of all branches that already exist in the system and admitting the addition of three new branches per existing route. As a result of the application of the CHA, Table 3.3 contains the selected equipments and their respective insertion years. Therefore, the CHA was able to reduce the list of candidate equipment from 558 to 30, reducing the number of candidate equipments in the search space given by Eq. (3.27) by more than 99%. It also important to notice that the application of the proposed CHA provides additional information about the possible insertion year which is itself a very valuable element because it leads to an additional reduction of the combinatorial degree of the problem. The equipments in this reduced list will then be used as the candidates to build the expansion plan.

Table 3.3: Equipments selected by the proposed Security CHA

Year	Equipment (From-to)
1	n_{68-116}, n_{77-78}, n_{12-117}, $n_{110-112}$.
2	n_{60-61}, n_{75-118}.
3	n_{8-5}.
4	n_{63-59}, n_{63-64}, n_{77-78}.
5	n_{8-9}, n_{9-10}, n_{64-65}, n_{2-12}.
6	n_{4-5}, n_{11-13}, n_{45-46}.
7	n_{77-80}, n_{4-11}.
8	n_{94-95}, n_{53-54}.
9	n_{38-65}, n_{38-37}.
10	n_{68-69}, n_{88-89}, n_{92-93}, n_{3-5}, n_{37-40}, n_{22-23}, n_{34-43}.

Thus, the TEP problem formulated according the AC model as in Case 1 was solved using the EPSO tool taking into account this reduced search space that was obtained by the Security CHA. The simulations used the same parameters of Cases 1 and 2, but now also considering the N-1 contingency criterion. Table 3.4 shows the solution obtained in this simulation.

Table 3.4: Results obtained by the hybrid approach.

CHA+EPSO Solution	
Solution plan	Year 1: n_{12-117}, n_{68-116}, n_{77-78} and $n_{110-112}$
Expansion cost (Mi USD)	225.38
Iterations	62
Computational time (h)	138.56

In order to verify the quality of the solution plan provided by the hybrid approach, the TEP problem was also solved using the entire search space (558 candidate equipments) and using the same parameters as before. The expansion plan obtained with the EPSO tool considering the entire search space is the same as it was obtained using the proposed hybrid tool and it is presented in Table 3.5 below.

Table 3.5: Results obtained using the entire search space.

EPSO Solution	
Solution plan	Year 1: n_{12-117}, n_{68-116}, n_{77-78} and $n_{110-112}$
Expansion cost (Mi USD)	225.38
Iterations	99
Computational time (h)	258.37

Therefore, using the proposed CHA to intelligently selecting interesting routes for expansion, it is possible to reduce the search space of the TEP problem, accelerating the convergence towards a good quality solution and reducing the computational time required by the EPSO to solve the TEP problem. Fig. 3.17 presents the convergence behavior when the EPSO is used to solve the TEP problem with and without the reduction in the search space.

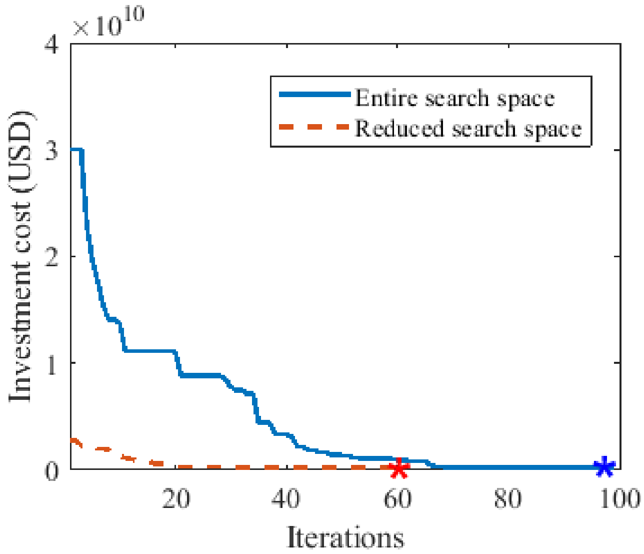

Figure 3.17: Convergence behavior of simulations in case 4.

According to Fig. 3.17 the solution of the TEP problem with the reduction of the search space using the proposed Security CHA provides a much better initialization of the particles when compared with the departing point of the algorithm not using the CHA. As a result, the number of iterations required to converge gets reduced and the computational time is reduced in about 47% while the final solution is the same as the one obtained without the CHA.

In order to verify the reduction of computational time obtained with the use of parallel computing, an iteration the Case 4 using the entire search space was performed. Thus, an iteration without the use of parallel computing took 7.93 h, and an iteration using the parallel programming takes in average 2.60 h according to the values in Table 3.5, that is, using parallel computing reduces the computational time in 67%. Table 3.6 summarizes computational time reductions that were obtained for the different tested approached. These reductions were obtained considering that the reference computational time is associated to the TEP problem using the AC OPF model.

Table 3.6: Comparing methods for reduce computational time

Approach	Reduction in the computational time
DC formulation	72%
Reduction of the search space using the CHA	47%
Parallel computing	67%
Reduction in the search space using CHA + Parallel computing	82%

3.8 Conclusions

TEP is a challenging problem and has been solved in several ways in the literature. In recent years, a lot of attention has been devoted to bio-inspired metaheuristics by the scientific community because of their efficient performance in solving extremely complex and combinatorial problems. These tools provide better results, both regarding the quality of the final solution and the computational time, when the initial solutions have already good fitness values.

Therefore, hybrid tools that use Constructive Heuristic Algorithms, CHA, to reduce search spaces (and consequently to get a good initialization of the solution algorithm) and metaheuristics used to refine the final solution plan can play an important role in identifying more robust expansion plans.

Regarding results of the simulations of Case 1, that is, TEP using the AC formulation, the EPSO tool presents a better behavior in finding a good quality solution than the GA and PSO tools. In this case study, EPSO was able to find the optimal solution in 70% of the simulations and it also presents a cheaper average cost over the ten simulations.

Regarding results of the simulations in Case 2, that is, TEP using the DC formulation, the optimal solution is cheaper than the one obtained in Case 1, and the computational time required to solve the TEP problem gets reduced by 72% regarding the value required by AC OPF models.

However, the DC model was not able to provide reliable solutions once the corresponding expansion plans originate violations of several constraints, namely non zero PNS values, when they are tested using the AC equations. Although DC models drastically reduce the computational time required to solve the TEP problem, they tend to underestimate the investments that are required to adequately expand transmission networks.

Finally, regarding results of the simulations in Case 4, that is, TEP using AC formulations and considering the N-1 contingency criterion, the proposed Security CHA was able to improve the search for good quality solutions by reducing the size of the search space and by providing better initialization to the solution algorithm. Furthermore, the reduction of the search space was able to reduce the computational time by 47%, the use of parallel computing by 67% and both techniques applied together can reduce the computational time by 82%. These two approaches proved to be very adequate and reliable to reduce the computational time required by TEP when compared to DC formulation models.

Chapter 4

Impact of DERs on Transmission Expansion Planning

> ...when you have an established scientific emergent truth, it is true whether or not you believe in it! and the sooner you understand that, the faster we can get on with the political conversations about how to solve the problems that face us...
>
> *Neil deGrasse Tyson*

4.1 Scope

This chapter starts by briefly addressing the main distributed energy resources mentioned in the literature and then it presents models to evaluate their possible impact on the TEP problems. It also includes results for the two developed models to address this issue.

In this scope, Section 4.2 presents, from different points of view, the concepts of distributed energy resources and their applications in power systems.

Section 4.3 introduces the distributed generation with their associated classifications. The different programs for demand response are presented in Section 4.4 and several technologies used in storage devices are quickly introduced in Section 4.5.

Some insights about electric vehicles and charging policies are discussed in Section 4.6 and several concepts on microgrids are introduced in Section 4.7.

Regarding the impact of the presence of distributed resources on TEP, this Chapter provides models to simulate the impact of solar distributed generation and the presence of large fleets on electric vehicles. The mathematical formulation of these problems are fully addressed in Section 4.8. The impact of solar distributed generation is detailed in Subsection 4.9.1 and Subsection 4.9.2 addresses the impact of electric vehicles on transmission expansion planning under several scenarios of penetration and charging policies.

Finally, Section 4.10 includes the main conclusions regarding the simulations results.

4.2 Distributed Energy Resources (DERs)

The introduction and dissemination of Distributed Energy Resources (DERs) can be considered as one of the major changes in power systems over the last years, with larger emphasis on distribution systems. These changes are associated to any device located in the distribution grid able to produce or store electricity or even modify the electricity consumption pattern seen by the transmission grid.

As mentioned in Section 2.11, there are different definitions for DERs in the literature. In (Akorede et al., 2010) DERs are considered as generation resources connected to the distribution systems, rather than in the bulk system. This view can be considered as rather conservative because DERs can also include demand response programs and the dissemination of electric vehicles, for instance.

Distributed generation can be based on conventional or non-conventional generators and the energy storage technologies can be based, for instance, on Battery Energy Storage (BES), flywheels, superconducting magnetic energy storage (SMES), compressed air energy storage (CAES) and pumped storage (PS), although the two last technologies are typically associated to larger installed capacities and so they would be connected more likely to transmission networks.

In this Chapter, DERs are considered in a wide sense, that is, not only associated to generation or storage resources connected directly to the distribution grids, but also related to energy efficiency programs and demand response, following the New York Public Service Commission (PSC) concepts.

Fig. 4.1 presents the DERs technologies. In this figure *Conv.Gen* represents conventional generation and *non-Conv.Gen* non-conventional generation, *PBP* means price based pro- grams and *IBP* incentive based programs. *Recip. Eng* stands for reciprocating engine, *MT* for micro- turbines, *CT* for combustion turbine. On the other hand, *EC devices* correspond to electrochemical devices, *PEMFC* is proton exchange membrane fuel cell, *PAFC* is phosphoric acid fuel cell, *MCFC* is molten carbonate fuel cell and *SOFC* is solid oxide fuel Cell. *Renew. Devices* represents the renewable units as photovoltaic (*PV*) and wind energy conversion systems (*WECS*). *BES* stands for battery energy storage, *SMES* represents the superconducting magnetic energy storage and *CAES* the compressed air energy storage.

According to these ideas, this Chapter provide basic concepts about the main DERs mentioned in the literature, namely Distributed Generation (DGs) in Section 4.3, Demand Response (DRs) in Section 4.4, Battery Energy Storages (BES) in Section 4.5 and Plug-in-Electric Vehicles (PEVs) in Section 4.6. Furthermore, the management of these resources under a microgrid environment is also briefly approached in Section 4.7.

4.3 Distributed Generations (DGs)

According to (Zhao et al., 2011) DGs are any generation units, typically ranging from 1 kW to 5 MW, located in the customer side or connected to the distribution grid. DGs

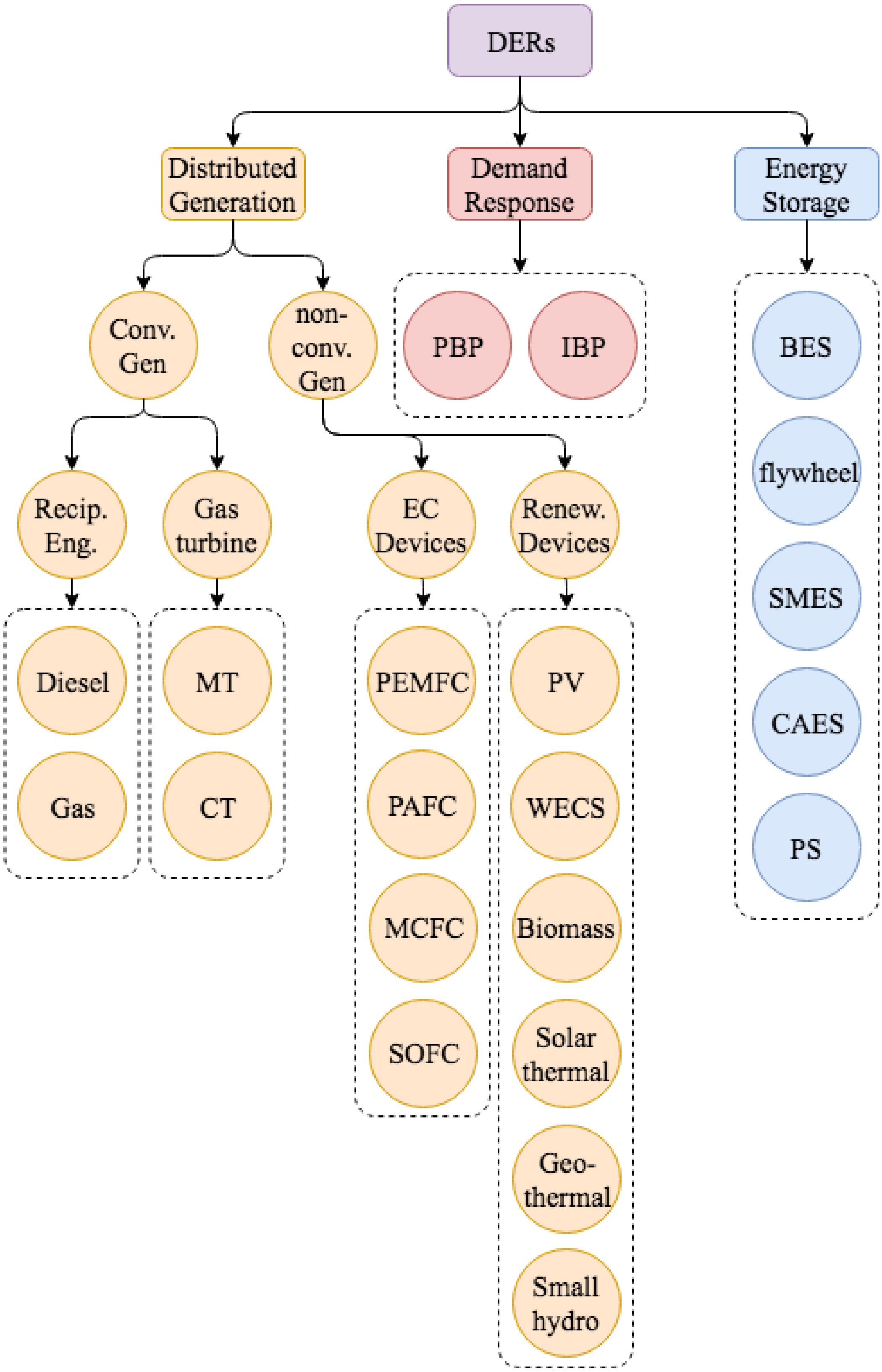

Figure 4.1: DERs technologies.

can be classified as renewable, as solar and wind power units, and as nonrenewable as internal combustion engine and micro-turbines. DGs can reduce the local load seen by the transmission grid and, therefore, they can contribute to postpone investments in new network equipments and eventually reducing network losses.

According to (Akorede et al., 2010), DGs can be classified in several groups regarding the technologies in use as follows:

i **Fuel cells (FCs)** - In this technology the electricity is obtained by chemical reactions. As in the batteries, FCs have two electrodes separated by an electrolyte. As can be seen in Fig. 4.1, there are different materials that characterize the FCs as the Proton Exchange Membrane Fuel Cell (PEMFC), the Phosphoric Acid Fuel Cell (PAFC), the Molten Carbonate Fuel Cell (MCFC) and the Solid Oxide Fuel Cell (SOFC). Fig. 4.2 presents the schematic block of a FCs. The fuel processor is responsible for removing fuel impurities, the power section (FC itself) is responsible for generating electricity and the power conditioning is responsible for the conversion of the direct current to alternating current;

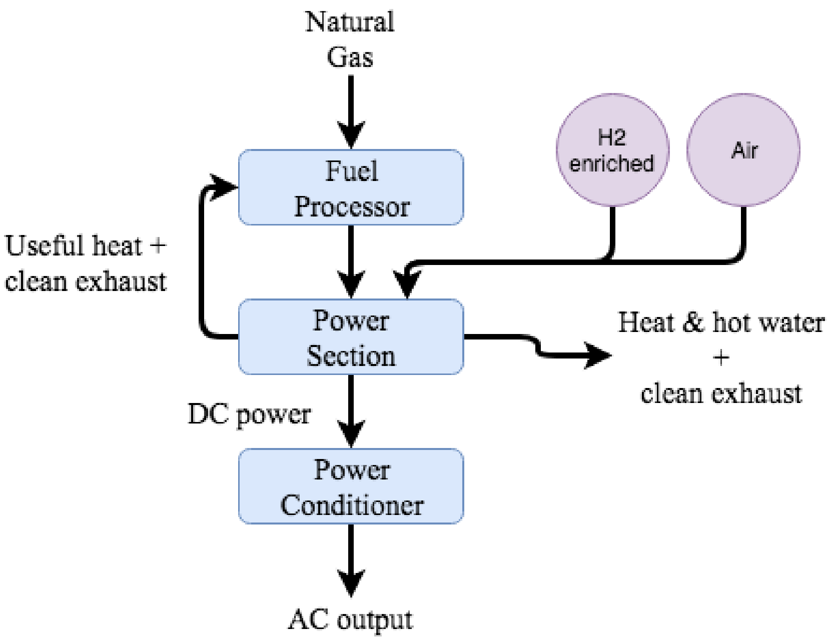

Figure 4.2: Schematic block for fuel cell

ii **Reciprocating engines** - This technology uses diesel and petrol engines to generate electricity from the movement of pistons in the cylinders. Although they present cheaper investment costs, the maintenance and operation costs are very expensive;

iii **Gas turbines (GT)** - They generate electricity from a flow of combustion gas. According to (Akorede et al., 2010), GTs can be classified in three groups, namely: heavy frame, aeroderivative, and micro-turbine;

iv **Photovoltaic systems (PVs)** - They convert solar energy into electricity and consist of arrays of cells connected in series or parallel. These systems can operate islanded from the main grid, for instance to supply remote communities, or connected to the

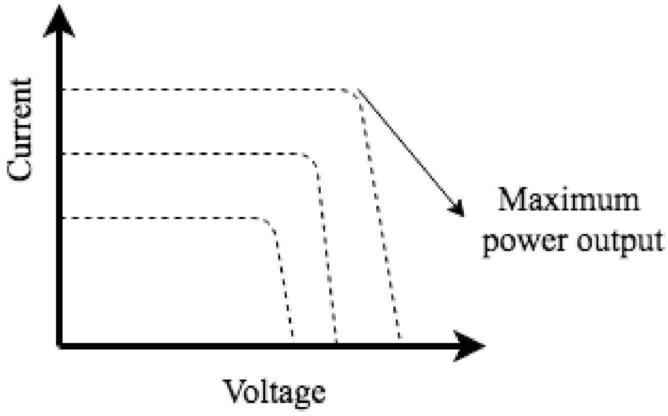

Figure 4.3: Typical characteristic of a PV module.

grid. PV systems typically need a large area to be installed, although there is not an uniform value for this relationship (m^2/kWp) because it depends on the local irradiation. In order to obtain the maximum power output, a maximum power point tracking is necessary in the converter. A PV module provides the maximum power output close to the knee of the characteristic curve illustrated in Fig. 4.3. It is important to note that the use of inverters can inject harmonics in the system, thus eventually degrading the quality of the wave (Akorede et al., 2010);

v **Wind energy conversion system (WECS)** - They are able to generate electricity from the kinetic energy of the wind. WECS correspond to the most disseminated among all the renewable technologies and by the end of 2016 the worldwide wind installed capacity reached 487 GW (Secretariat, 2017). However, the power quality can be compromised if the generator is directly connected to the network.

vi **Solar thermal** - This technology transforms solar energy into heat. Generally, it is used a system to concentrate the solar radiation, like mirrors for example, in a vessel with fluid. In this way, the fluid reaches high temperatures and its vapor can then be used to drive a turbine coupled with a generator, for example.

vii **Geothermal** - This type of technology uses the heat of the earth to produce electricity. Deep holes are made in the soil in order to find a suitable geothermal hot spot. The steam is then piped to a turbine coupled with a generator.

viii **Small hydro-turbines** - As in larger hydro systems, they use the flowing water to generate electricity. The capacity to store water is usually very reduced and the installed capacity is also reduced when compared with hydro units connected to transmission systems.

ix **Biomass** - It is an important renewable energy technology that uses organic material from plants and animals to produce electricity. According to (Akorede et al., 2010) this can be accomplished using animal residues, industrial residues, sewage, municipal solid waste and residues from agriculture and forestry crops.

In several countries, renewable DGs are still incipient and may require some kind of incentives as feed-in-tariff or net metering to reach significant levels. While the Feed-in Tariff scheme has been widely applied in the past, it has now become less justified mainly due to the sharp decline of the photovoltaic system costs and also given the maturity reached by wind systems. Consequently, the Net Metering scheme is being adopted in several countries, such as in Brazil, where it is in force since 2012 under the Normative Resolution 482 (NR482). However, this incentive was not enough to ensure the economic viability of investments on DG units in Brazil mainly due to several taxes that are applied on the electricity produced by DGs. Therefore, in April 2015, it was published the Agreement 16 in order to reduce the mentioned taxes on DGs.

In this context, the adoption of government subsidies and support strategies was extremely important to boost the penetration of PV systems in the distribution network in Brazil, as illustrated in Fig. 4.4. This figure shows the cumulative penetration of DG PV units in residential consumer installations in Brazil over the last years. It is clear that an adequate incentive structure for PV systems will very much favor its penetration. Note that the PV penetration in the residential market, which was barely noticeable after the publication of RN482 in 2012, was significantly boosted by the Agreement 16 in 2015.

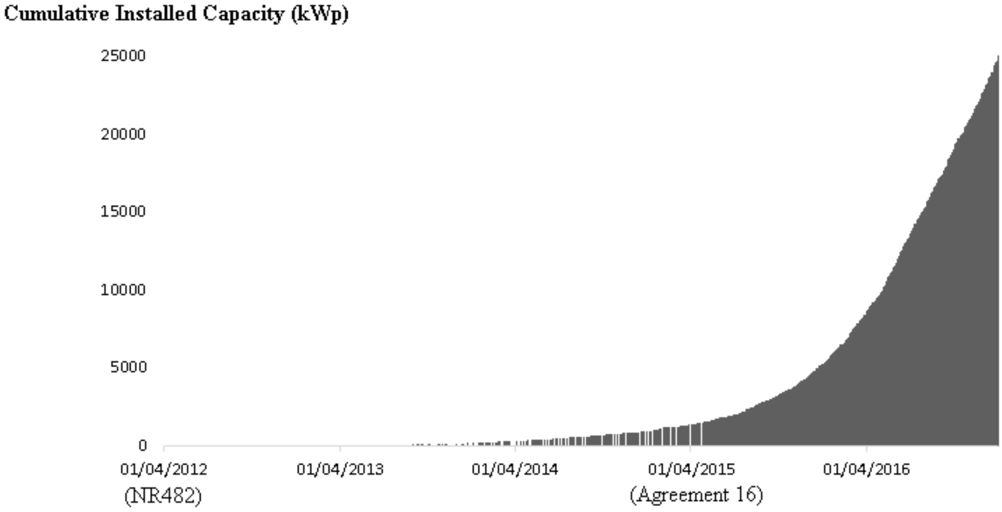

Figure 4.4: Cumulative PV penetration on Brazil for residential consumers (kWp is related to peak)

Still regarding the Brazilian case and the spread of DGs units over the country, the study reported in (Gomes et al., 2018a) estimates the minimum monthly residential demand for prosumers located in the different distribution concession areas in the interconnected Brazilian system so that it is ensured the economic viability of the installation of PV systems. This demand is termed as *threshold demand* and Fig. 4.5 provides its value for each concession area. The mentioned publication indicates that grid parity was obtained for 49 of the 63 DisCos that exist in the interconnected Brazilian system.

Thus, using these results it was possible to estimate the number of consumers that are potential investors in PV systems. This means that for these consumers the investment in PV systems is economically feasible, that is, the respective Levelized Cost of Energy (LCOE) is below the current tariff applied to these consumers, if they were supplied by the grid. For each Brazilian region in which the interconnected power system is organized

(North, Northeast, Midwest, Southeast and South), Fig. 4.6 presents the average threshold demand and the estimate of the number of potential investors on PV systems.

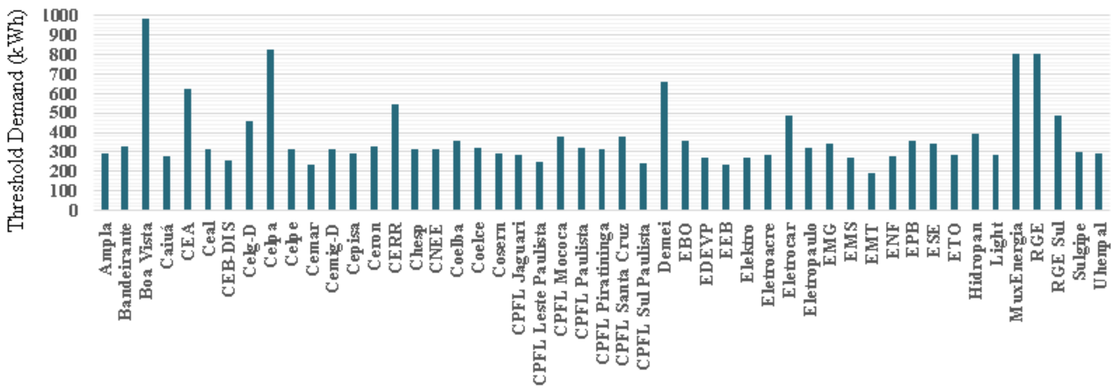

Figure 4.5: The threshold demand for of each Brazilian DisCo.

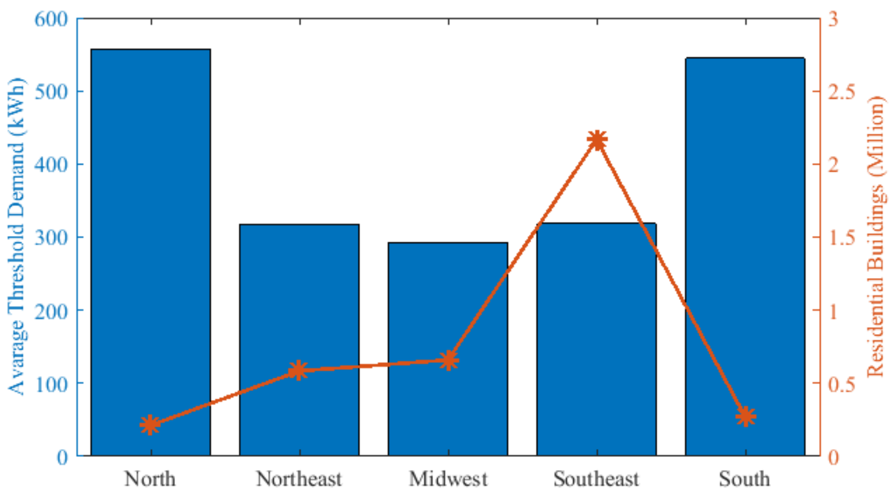

Figure 4.6: Potential investors and the average threshold demand by region in Brazil.

Therefore, DG penetration is higher when a strong political incentive is adopted and can display important regional variations. This impact, namely on a regional basis, should be taken into account in the transmission expansion planning studies in order to get all the benefits from the dissemination of DERs, namely regarding the possibility of postponing investments in new network equipments and facilities. This investment postponing will then have an impact on the electricity network tariffs to be paid by end consumers to remunerate transmission of distribution companies.

4.4 Demand Response Programs (DRs)

According to (Albadi and El-Saadany, 2008) demand response is related to changes in the end-use customers electricity behavior as a reaction to changes transmitted by electricity price signals. Demand response programs can be classified as Price Based Programs (PBP) and as Incentive Based Programs (IBP). The PBP group is based on dynamic price rates, in which the rates fluctuate according to the electricity prices and network operation conditions in real time. The idea behind price based programs is to smooth the demand curve by setting a higher price during peak periods and lower prices during off-peak periods. The most common mechanisms used are Time of Use (ToU), Critical Peak Pricing (CPP), Extreme Day CPP (ED-CPP), Extreme Day Pricing (EDP) and Real Time Pricing (RTP).

Regarding the IBP group, it can be further classified in classical or market based programs. Classical approaches include direct load control and curtailment load programs. On the other hand, market based approaches include demand bidding, emergency demand response, capacity markets and ancillary services market programs, as presented in Fig. 4.7.

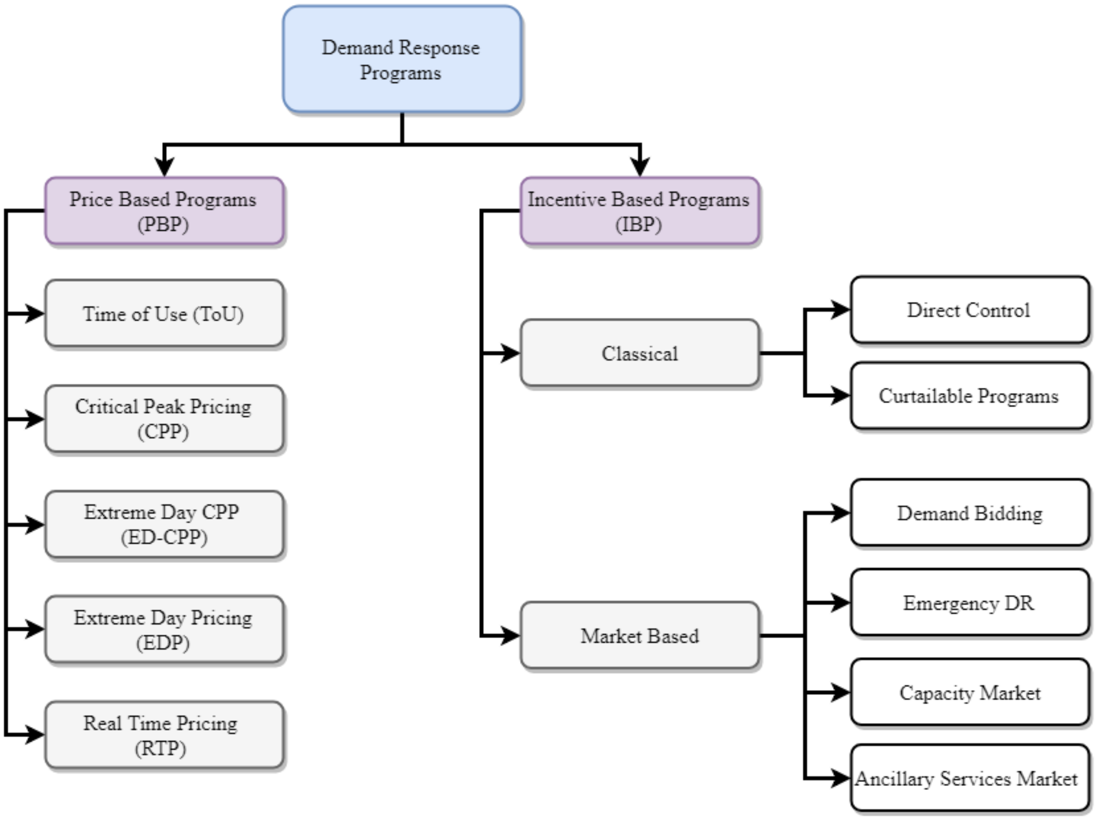

Figure 4.7: Classification of DR programs.

Also according to (Albadi and El-Saadany, 2008), the benefits from DR programs can be associated to the participants, can be related to market-wide issues, to reliability enhancement or can contribute to improve the market performance as shown in Fig. 4.8.

Participants can save money in their electricity bills due a change in the electricity consumption behavior. Additionally, the electric infrastructure is used in a more efficient way and, because of that, an overall reduction in the price of electricity can be experienced.

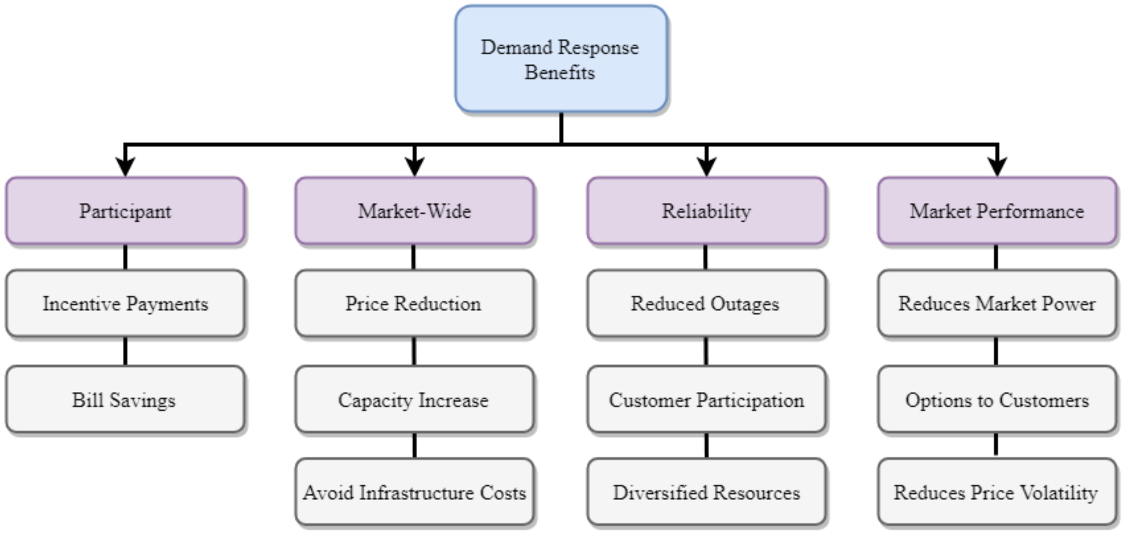

Figure 4.8: Benefits associated with Demand Response programs.

The long term impact of the increased efficiency in using several components of the power system should also be computed for market-wide purposes. In fact, the mentioned increased efficient use of the system can enable the postponement of investments on new equipments on the distribution/transmission grid thus reducing network costs and ultimately reducing the final end user tariffs.

Furthermore, the system operator can increase its spectrum of resources to maintain reliability at desired levels. Finally, the market performance is also increased because under DR programs consumers can manage at least partially their consumption and therefore they will be in a better position to provide services namely in terms of participating in some specific reserve auctions as they already exist, for instance, in the UK.

4.5 Energy storage technologies

Some renewable technologies as solar and wind power are typically associated to some level of intermittence in the output power, which can be drastically reduced if there is an associated storage device. Besides, storage devices when they are located in the distribution network can also provide ancillary services (Divya and Østergaard, 2009) and help operating these networks regarding possible overload and voltage problems. Finally, storage devices can also be used from an user point of view to reduce the peak power supplied by the grid, for arbitrage purposes or to provide services to the network providers. The dissemination of storage devices at the end user level is still far from taking place because of the involved investment cost, but recent research suggests that more than one stream of money should be considered in order to more easily break even (Metz, 2017).

The next paragraphs provide some brief indications regarding the most common storage technologies. More complete information on storage technologies can be obtained in (Akorede et al., 2010) and on (Metz, 2017).

i **Battery energy storage system (BESS)** - they can provide quick response to load changes or transmission equipment failures, and for this reason, they can be used to provide spinning reserve, apart from the usual applications of storage technologies. BESS stores chemical energy and can be built as lead- acid batteries, nickel-metal hybrid batteries, lithium ion batteries, flow batteries, high temperature batteries, etc.

ii **Flywheels** - It is an electromechanical storage system that stores kinetic energy in a rotating mass. When required, this energy can be used to supply a generator that will produce electricity. In recent years, flywheels have been mainly used to regulate the frequency in the electric grid, namely in isolated systems associated to wind generation.

iii **Superconducting magnetic energy storage (SMES)** - SMES is a device capable of absorbing energy under the form of a magnetic field. When required, this energy can be injected back to the network. Typically, these systems require a low operation temperature and still have a large investment cost, although their efficiency is reported to be above 90% (Akorede et al., 2010).

iv **Compressed air energy storage (CAES)** - CAES is a technology in which energy is stored through the air compression in an underground geological reservoir or in specially built reservoirs. This air compression is typically done in off-peak periods. In peak periods, this compressed air is conducted through pipes to a turbine that moves a generator. Currently there are two industrial installations of this type in the world, one of them in Huntorf, Germany, with the installed capacity of 320 MW and the other one in Alabama, USA, with 110 MW.

v **Pumped storage** - This type of storage uses electricity in off-peak periods to pump water from a lower level reservoir to a higher level one. This way water can be dispatched down again at peak periods. This storage technology is still the most wide spread one, corresponding to more than 95% of the total storage installed capacity. Although these installations are associated to large hydro units, therefore connected to upper voltage level networks, it is included here in order to provide a more complete overview on storage technologies, namely regarding the one that is still the most disseminated worldwide.

4.6 Plug-in-Electric Vehicles (PEVs)

Electric vehicles will certainly play an important and increasing role in the transport sector over the next years. As their number grows, they will affect the behavior of the electricity demand seen not only by distribution but also by transmission networks. This means that the operation and expansion planning of the power systems will also be impacted by the increasing number of PEVs.

Electric vehicles are commonly characterized as vehicles that use an electric motor to hand over mechanical shaft power (Morais et al., 2014). PEVs have different demands depending on their technology and they will change the system demand according to the different needs of their owners, the charging policies that are used/proposed by electricity retailers, the level of their penetration and the availability of charging installations.

The next paragraphs briefly discuss several aspects that influence the impact of the PEVs on the system demand.

A. PEVs Penetration

The penetration of PEVs must be predicted along the planning horizon of a TEP study as well as the location of future charging stations. The network needs to be prepared to meet this new future demand which means that this information has to be internalized in expansion and operation planning studies. PEVs penetration scenarios are a key element to identify their charging impact on the grid. Besides, due to its behavior as V2G or G2V, proper business models should be proposed and adopted to model the controllability of EVs.

B. Charging Policies

The charging policies have a direct influence on the decision of the PEVs owner, although sometimes this decision is transferred to a third agent called parking lots (Neyestani et al., 2015). In this case, the PEVs user must indicate the level of energy that should be stored during a specific time. Among the various classifications of charging strategies, the literature mentions the following policies:

- Uncontrolled charging;
- Multiple Tariffs;
- Smart charging;
- V2G services.

In the uncontrolled charging, PEV owners connect the vehicle to the grid when the last trip is finished or when a charging point is available. In the multiple tariffs policy, the retailer offers different tariff levels (at least organized in two levels, that is, peak periods with higher prices and off peak with lower prices) to induce consumers to shift the demand to off-peak. In the smart charging, the retailer or the grid operator control the time and the charging process of the PEVs and, as a result, smart charging generally leads to a valley-filling effect. Finally, V2G services are an extension of smart charging in the sense that the vehicles will not be restricted to buy electricity from the grid to charge their batteries but can also provide services to the grid, either in terms of discharging in peak periods or participating in specific reserve markets, for instance (Hatziargyriou et al., 2013).

C. Availability of Charging

The charging infrastructure has to be considered given its impact on the system. The results of studies on the penetration of PEVs should be used to adequately plan the location of charging infrastructure so that it is ensured they are available when required and as the number of EVs increase. This wide spread availability will definitely increase the confidence level of consumers and so contribute to increase the penetration level. The availability of this charging infrastructure will also impact on the demand at the regional level and thus it will influence the expansion planning and operation of distribution and transmission networks.

4.7 Microgrids (μGs)

Different DER installations can be aggregated with a distribution network and a set of loads together with control capabilities over some of these units leading to the concept of microgrid (Khodaei and Shahidehpour, 2013). Therefore, a microgrid is a system containing at least one DER and one load that can eventually operate in an islanded mode from the main grid for a period of time that depends on the capacity of the local generation and storage devices and the degree of control that exists over the loads. The main goal of a microgrid is to ensure the secure and integrated operation of this aggregation of devices and equipments both in the normal operation mode (when the microgrid is interconnected with the rest of the system) as well as in an island mode, if this operation mode is possible from a legal and regulatory point of view.

A typical microgrid structure usually contains a DG unit, an Energy Storage System (ESS) and a Point of Common Coupling (PCC) with the rest of the system in which the island mode can be originated, for economic or reliability goals. Fig. 4.9 provides an illustration of such a structure.

Microgrids can improve the reliability of the grid while reducing the investment costs in new equipments for both distribution and transmission grids. This ultimately means that this increased operation flexibility (namely if the operation in an islanded mode is allowed from a legal point of view) should be internalized in expansion distribution and eventually also in transmission planning activities.

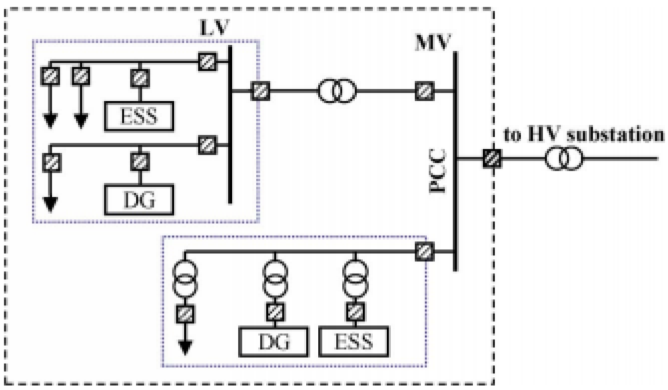

Figure 4.9: Common microgrid structure. From (Khodaei and Shahidehpour, 2013).

4.8 Mathematical formulation of the TEP problem

This Chapter details the results of two simulations in order to analyse the impact of DERs on the TEP problem, namely the impact of solar DG and of PEVs, because as indicated above these equipments impact on the demand seen by transmission networks. Therefore, the simulations follow the steps described below:

i The hourly electricity demand along the entire planning horizon is increased considering the annual growth rate specified for the electricity demand;

ii Estimate the hourly electricity energy along the entire planning horizon exclusively due to the distributed energy resources penetration considered for the period under analysis. In this case the PV generation and the generation from PEVs (in V2G services) are considered as negative demand;

iii Add up the two demand components calculated in steps i and ii and obtain the global hourly electricity demand for the entire planning horizon;

iv From the yearly demand profiles built in step iii, extract the worst case of electricity demand corresponding to the yearly peak demand. This demand scenario corresponds to the mostly used in the literature, as in (Mendonca et al., 2013) and (Braga and Saraiva, 2005), and its adoption means that if the system is able to meet the peak yearly demand along the planning horizon, it will also be able to meet any other electricity demand scenario;

v Solve the TEP problem using the yearly peak demand values obtained in step iv;

In this way, based on the changes introduced in step ii due the DERs penetration, it is possible to evaluate their impact on the TEP problem.

The mathematical formulation of the TEP problem adopted in the simulations detailed in this Chapter takes into account the minimization of the objective function OF given by Eq. (4.1) which includes the investment cost on new transmission and network equipments and a penalization term for Power Not Supplied (PNS). In (4.1) $C_{inv,p}$ is the investment cost in period p, β_1 is the penalization factor for Power Not Supplied in period p (PNS_p) and κ_p is the present worth coefficient given by Eq. (4.2) in which d is the discount rate. As indicate in Chapter 3, this problem is constrained by physical, financial and quality of service constraints.

$$OF = \sum_{p=1}^{np} (C_{inv,p} + \beta_1 . PNS_p) . \kappa_p \tag{4.1}$$

$$\kappa_p = \frac{1}{(1+d)^p} \tag{4.2}$$

Therefore, considering the annual peak demand for the entire planning horizon taking into account the impact of DERs penetration, the TEP problem aims at identifying and locating along the horizon the network equipments as transmission lines, cables and transformers, that should be inserted on the grid so that the investment cost is minimized while ensuring and adequate quality of service. The Power Not Supplied (PNS) associated to each tested solution is calculated using the AC-OPF model, described in Section 3.2.1, over the peak demand distributed by the system nodes in order to check the feasibility of each candidate solution. For each candidate solution, the mentioned AC-OPF problem should be solved for each period of the planning horizon considering in each of them the network equipments that are scheduled to be inserted in that period and that are included in the solution under analysis. The adopted AC-OPF was already detailed in Chapter 3 and is provided below from Eq. (4.3) to Eq. (4.12) to facilitate reading this Chapter.

$$Minimize \sum_{ger=1}^{nger} F_{ger}(P_G^{ger}) + \sum_{bus=1}^{nbus} (1-\alpha_{bus}) P_D^{bus}.C_{def}^{bus} \tag{4.3}$$

Subject to:

$$P(V,\Theta,n)_{bus} - P_G^{bus} + \alpha_{bus}.P_D^{bus} = 0 \tag{4.4}$$

$$Q(V,\Theta,n)_{bus} - Q_G^{bus} + \alpha_{bus}.Q_D^{bus} = 0 \tag{4.5}$$

$$P_{G_{min}}^{ger} \leq P_G^{ger} \leq P_{G_{max}}^{ger} \tag{4.6}$$

$$Q_{G_{min}}^{ger} \leq Q_G^{ger} \leq Q_{G_{max}}^{ger} \tag{4.7}$$

$$V_{min}^{bus} \leq V^{bus} \leq V_{max}^{bus} \tag{4.8}$$

$$(N+N^0)S^{from} \leq (N+N^0)S^{max} \tag{4.9}$$

$$(N+N^0)S^{to} \leq (N+N^0)S^{max} \tag{4.10}$$

$$0 \leq n \leq n^{max}, n \in \mathbb{Z}_+ \tag{4.11}$$

$$0 \leq \alpha \leq 1 \tag{4.12}$$

In this formulation, Eq. (4.3) is the objective function to be minimized in which the first term corresponds to the total generation cost and the second term is the deficit cost due Power Not Supplied. Eq. (4.4) and (4.5) are the real and reactive nodal power balance equations. To ensure that at least one solution exists for the AC-OPF, the loads are considered dispatchable that is, the loads are modeled with a flexibility variable, α, which means the problem has enough flexibility to reduce the demand in node *bus* (active and reactive demand with the same proportion to keep the power factor unchanged) if this is required to ensure the feasibility of the problem.

Eq. (4.6) and (4.7) are the real and reactive generation limit constraints, Eq. (4.8) is the voltage limit constraint, Eq. (4.9) and (4.10) ensure that the apparent power flow in each branch complies with the transmission limits. These constraints are established using matrices N_o and N that include information on the base topology of the transmission system and on the new equipments associated to the expansion plan associated to a specific particle considered in the EPSO algorithm, This means that when running this AC-OPF problem for a specific period, the new equipments are inputs to this problem and are related to the expansion plan associated to a particle of the EPSO algorithm.

This also means that for each right of way, the parameter n_{ij} is also an input to the AC-OPF problem and is related with the expansion plan associated with a particle of the EPSO algorithm. Eq. (4.11) imposes the maximum number of new equipment (integer variable) to be inserted in a right-of-way and Eq. (4.12) imposes the load reduction flexibility range from 0 to 1. Note that when α is 1 there is no PNS and the tested system configuration is able to supply the entire demand. On the other hand, any value from 0 to 1 indicates that there should be Power Not Supplied to ensure the feasibility of the problem.

4.9 Numerical simulations

In recent years, power systems have been watching important advancements related with PEVs, DRs, DG, Microgrid and Smart Grid installations that directly affect distribution networks while impacting indirectly on transmission studies. These changes will lead to an extra flexibility on the transmission-distribution boundary and to a significant modification of the load patterns, that are an essential input to planning studies. In this scope, this section describes two simulations that incorporate the impact of distributed generation and PEVs on transmission expansion planning.

In both simulations, TEP is conducted using a dynamic multiyear approach using the AC-OPF model, described in Section 3.2.1, to get insights on the system operation conditions. Besides, in both simulations the planning problem is solved using the EPSO algorithm, described in Section 3.5.3.

As mentioned above, the simulations presented in this section were conducted using the same mathematical formulation so that it is possible to evaluate the impact of the mentioned DERs on the TEP problem given the changes introduced in the system demand pattern.

Finally, both simulations used the same modified version of the IEEE RTS 24 bus system. The simulations were run in MATLAB with an Intel i7, 3.4GHz, 8 GB RAM. The system that was used has some differences regarding the available in Appendix A.0.1, as described below:

i the loads are modeled as negative real power injections with associated negative costs as described in (Zimmerman et al., 2011);

ii the values of all the loads were duplicated and the installed capacity of all generators was tripled (real and reactive) in order to turn the transmission network more stressed. Therefore, the initial peak demand is 5700 MW and the total generation capacity is 10215 MW.

4.9.1 Impact of solar DGs on Transmission Expansion Planning

In this simulation the penetration of solar DG was organized in 4 scenarios: 0%, 10%, 15% and 20% of the annual peak demand connected to each bus. After the optimization process carried out by the EPSO algorithm is done (considering the new peak demand for each scenario), the DG impact is analyzed considering three items: economic aspects, losses and environmental aspects.

Regarding the economic analysis, four load blocks representing one day of each season of the year are used in order to estimate the operation costs, the transmission losses and the CO_2 emissions. Each bus of the system has its own demand profile and these values can be assessed in Appendix A.0.1 taking into account the Monday of the 2nd week for the Winter, the Saturday of the 13th week for the Spring, the Friday of the 24th week for the Summer and the Sunday of the 41st week for Autumn.

In TEP problems DG is usually modeled as a negative real load, that is, the DG reduces locally the real load on a primary substation. Fig. 4.10 new load profile over one day (24 hours) of the bus 1 assuming a 10% DG penetration on the test system used in this chapter. This new demand will be used to carry out the expansion planning studies. In this simulation, the maximum solar generation (solar peak at 12:00) for each bar is assumed to be proportional to its annual peak load. As an example, Fig. 4.11 presents the DG generation in MW in each bus for the three penetration levels that were considered, 10%, 15% and 20%. As a whole, the 10% level of penetration is associated to an installed capacity of 570 MW, 15% is associated to 855 MW and 20% to 1140 MW for the annual peak demand of 5700 MW considered in the first year.

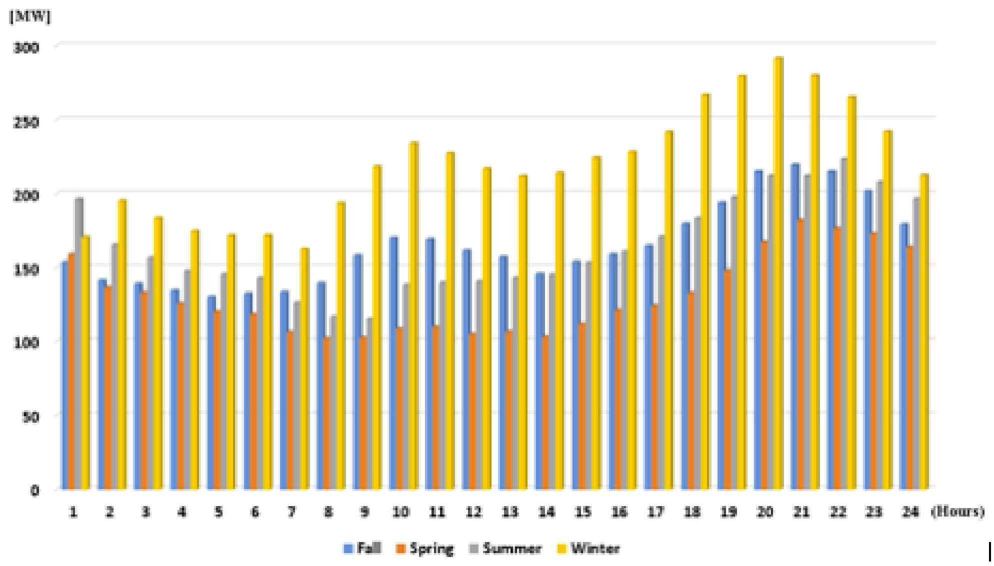

Figure 4.10: New load profile for the bus 1 (with 10% DG penetration).

Regarding the CO_2 emissions, we use data from (Correa et al., 2013) indicating for each generation technology the level of CO_2 emissions per generated MWh. The load growth was set at 2,5% per year and the discount rate was set at 5% per year, the number

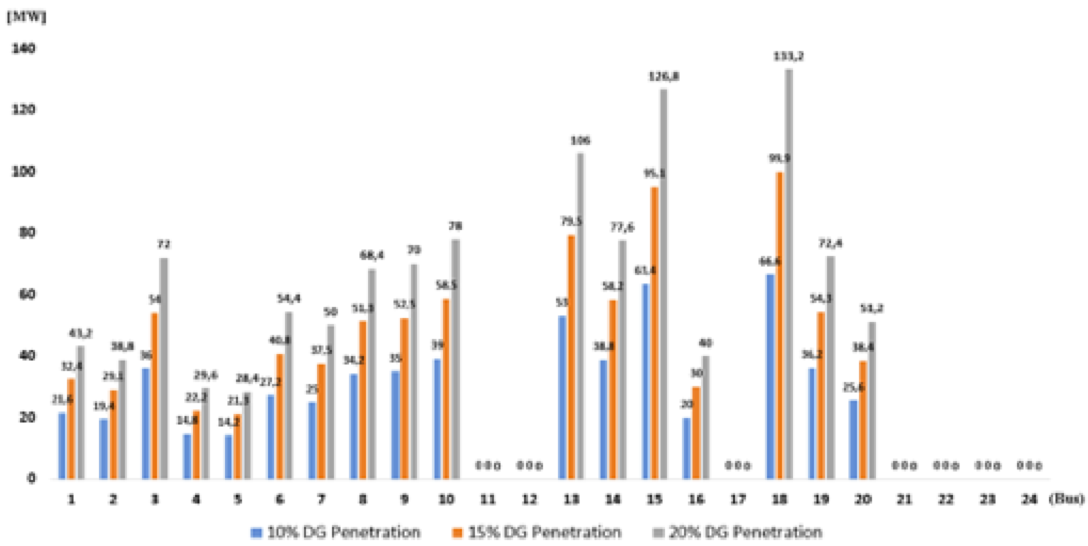

Figure 4.11: DG penetration by bus and scenario at 12 am (Peak of solar generation).

of particles in each population of the EPSO algorithm was set at 50, the planning horizon is 3 years and the PNS penalization cost was set at 10^9 USD/MW. The EPSO algorithm stops after running 50 iterations with the same best solution.

Regarding the simulations results, as the annual peak load for this system occurs after 6 pm, the solar distributed generation has no impact in decreasing it since no associated storage devices are being considered. Additionally, the optimization process takes into account only the minimization of the investment cost for new equipments on the grid while ensuring that the annual peak demand is supplied. Therefore, for the considered cases (solar DG penetration of 0%, 10%, 15% and 20%) the annual peak demand is the same which means that the optimal expansion plan identified by the EPSO algorithm remains unchanged. This plan was obtained running 112 iterations in 42 minutes. For each analyzed case Table 4.1 provides the values of operation costs, transmission losses and emissions using the four load blocks to analyze the impact of PV DG in the obtained expansion plan.

Table 4.1: Comparison of the results for the 4 DG penetration scenarios.

Cases	DG penetration	Inv. Cost (Mi USD)	Op. Cost (Mi USD)	Trans. Losses (MWh)	Emissions (tCO_2)
1	0%	98.05	47.60	14808.07	62131.47
2	10%	98.05	39.08	14072.61	51495.52
3	15%	98.05	35.43	13690.19	47620.69
4	20%	98.05	32.47	13372.85	43649.91

The best solution found by the EPSO algorithm corresponds to the installation of the following equipments: - year 1 - one transformer between bus 3 and 24, one 138 kV cable connecting bus 6 to 10, one 138 kV line connecting buses 7 to 8; - year 2 - one 138 kV line connecting buses 1 to 5. These equipments allow the system to gain flexibility enough to accommodate the demand in Period 3 so that no new equipment is required in this final period.

As solar distributed generation reduces the local load, the generation required by thermal plants is reduced and, consequently, the costs associated with the operation of the system also decrease, as well as the CO_2 emissions and the transmission losses.

4.9.2 Impact of PEVs on Transmission Expansion Planning

In this simulation, the planning problem considers four scenarios for the PEVs charging policies (uncontrolled, multiple tariffs, smart charging and V2G), four scenarios for the availability of charging in uncontrolled charging policy and three scenarios for the penetration level (likely, optimistic and aggressive). Therefore, the TEP problem is solved 22 times (21 scenarios associated to the PEVs and a base case scenario not considering PEVs).

The planning horizon includes 10 years and in the simulations we used a penalization factor for PNS equal to 10^9 USD/MW, the number of particles in the population was set at 30 particles, a discount rate of 5% and a load growth of 2.5% per year were admitted. Besides, the scenarios for the PEV evolution and its impact on the system demand were extracted from (Hatziargyriou et al., 2013) using the German case in which a stochastic EV demand simulation methodology was employed on an hourly basis.

The penetration scenarios that were considered are indicated in Table 4.2 and the scenarios for charging availability (only considered for uncontrolled charging) are presented in Table 4.3. Finally, in the multiple tariffs scenario we specified that the lower tariff period goes from 10 pm to 6 am.

Table 4.2: PEVs penetration scenarios

	Penetration scenarios over the planning horizon		
	Likely	Optimistic	Aggressive
PEVs	414.000	847.000	1728.000

Table 4.3: Availability of charging

Availability of charging for uncontrolled charging			
Model 1(M1)	Model 2 (M2)	Model 3 (M3)	Model 4 (M4)
100% home	75% home 25% work	50% home 50% work	25% home 75% work

Under the above conditions, the additional demand for each of the 21 scenarios is displayed in Fig. 4.12 to Fig. 4.32. These values are calculated for the last year in the horizon when the cumulative PEV penetration assumes the largest value.

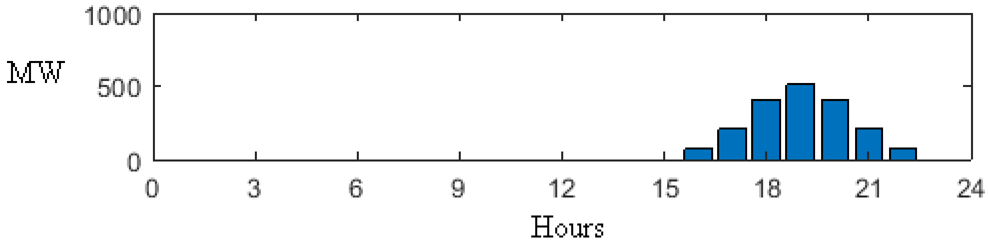

Figure 4.12: Impact of PEVs on the system demand - Uncontrolled - Likely - M1.

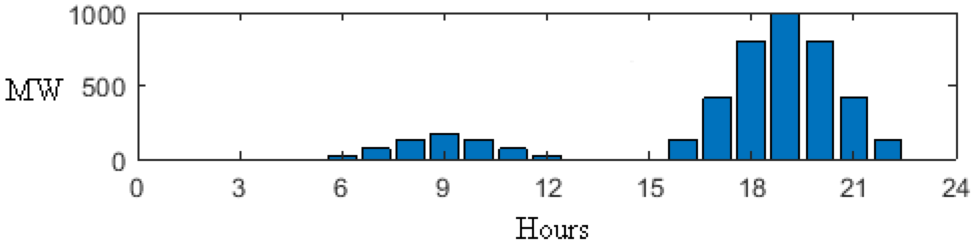

Figure 4.13: Impact of PEVs on the system demand - Uncontrolled - Likely - M2.

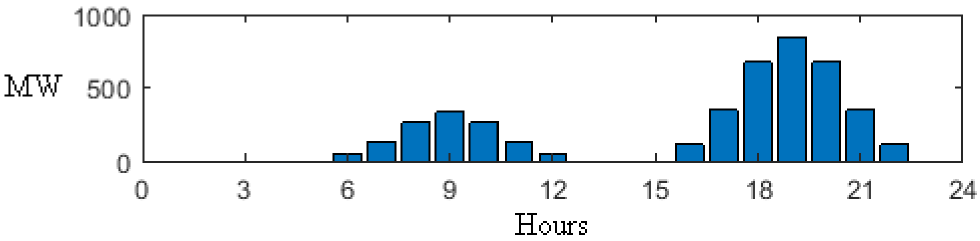

Figure 4.14: Impact of PEVs on the system demand - Uncontrolled - Likely - M3.

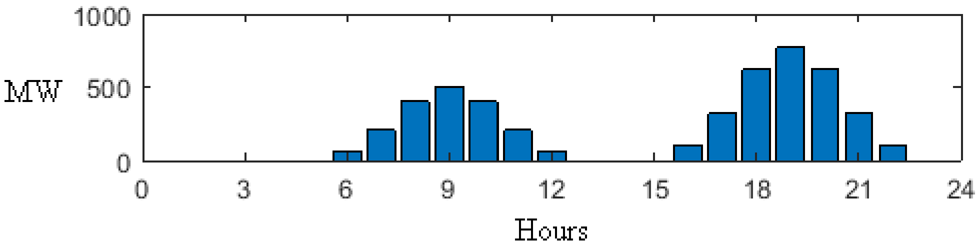

Figure 4.15: Impact of PEVs on the system demand - Uncontrolled - Likely - M4.

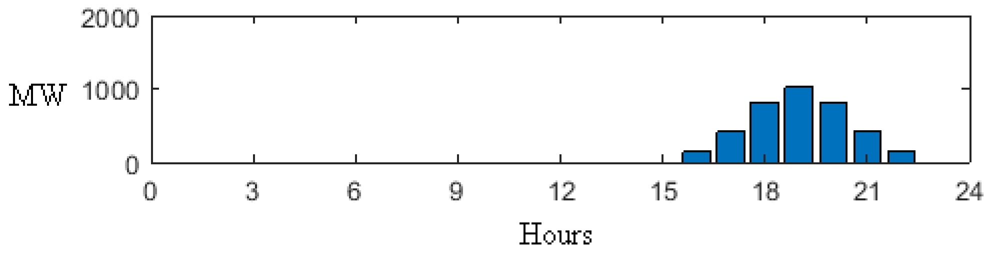

Figure 4.16: Impact of PEVs on the system demand - Uncontrolled - Optimistic - M1.

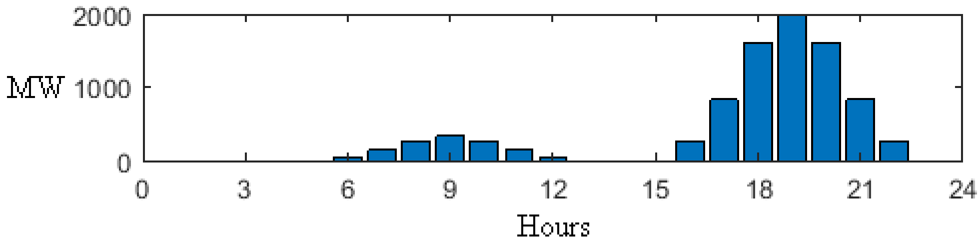

Figure 4.17: Impact of PEVs on the system demand - Uncontrolled - Optimistic - M2.

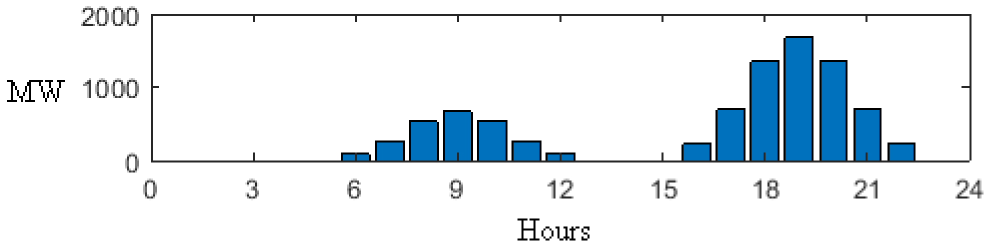

Figure 4.18: Impact of PEVs on the system demand - Uncontrolled - Optimistic - M3.

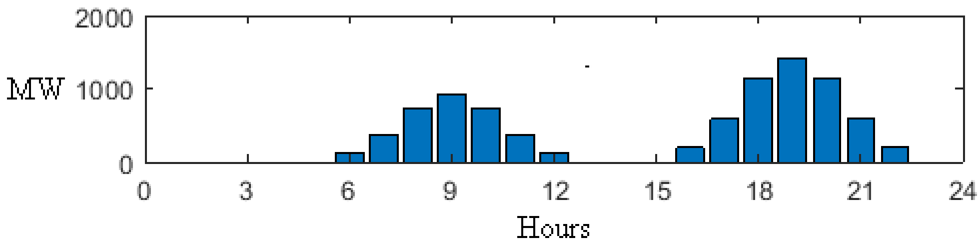

Figure 4.19: Impact of PEVs on the system demand - Uncontrolled - Optimistic - M4.

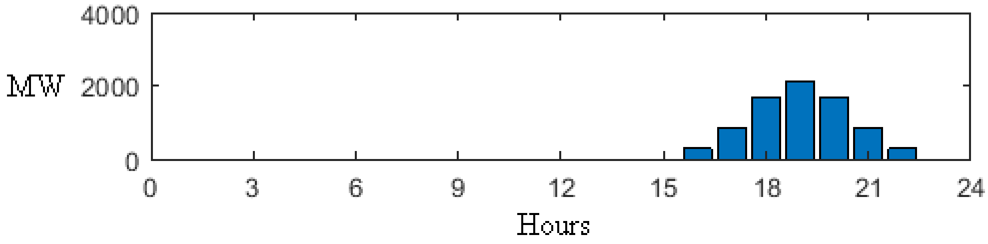

Figure 4.20: Impact of PEVs on the system demand - Uncontrolled - Aggressive - M1.

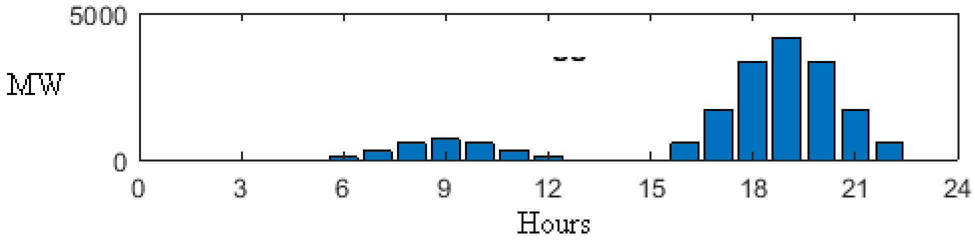

Figure 4.21: Impact of PEVs on the system demand - Uncontrolled - Aggressive - M2.

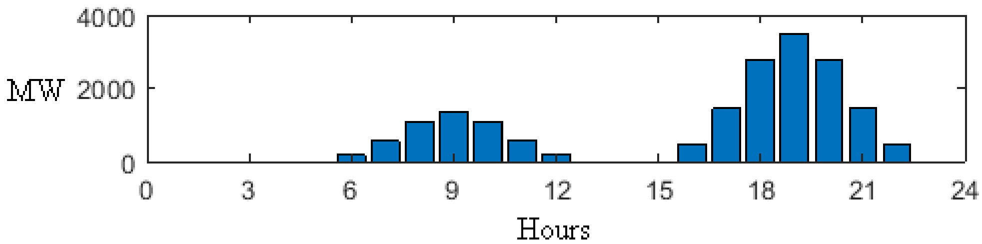

Figure 4.22: Impact of PEVs on the system demand - Uncontrolled - Aggressive - M3.

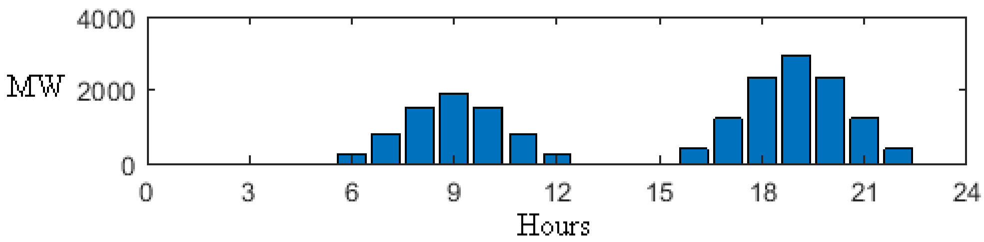

Figure 4.23: Impact of PEVs on the system demand - Uncontrolled - Aggressive - M4.

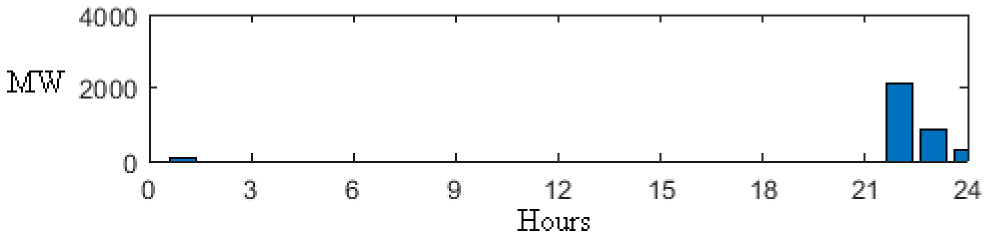

Figure 4.24: Impact of PEVs on the system demand - Multiple Tariff - Likely.

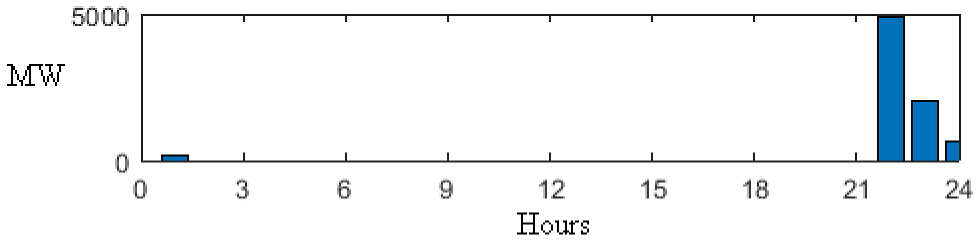

Figure 4.25: Impact of PEVs on the system demand - Multiple Tariff - Optimistic.

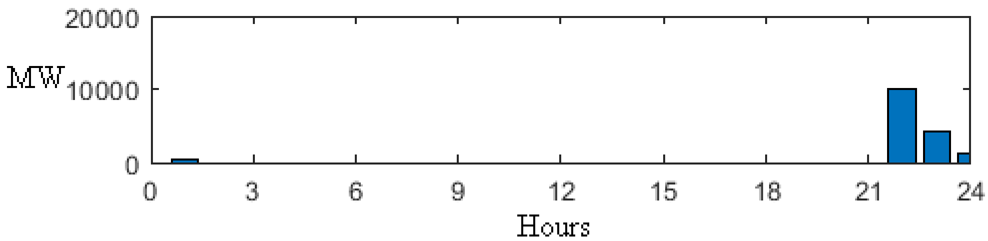

Figure 4.26: Impact of PEVs on the system demand - Multiple Tariff - Aggressive.

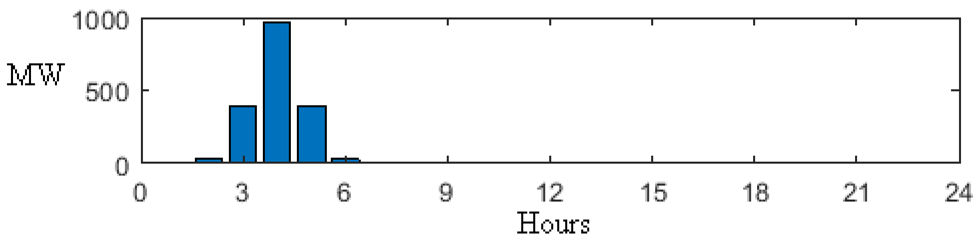

Figure 4.27: Impact of PEVs on the system demand - Smart charging - Likely.

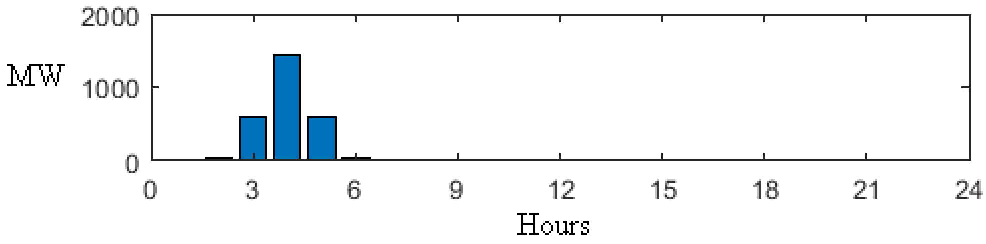

Figure 4.28: Impact of PEVs on the system demand - Smart charging - Optimistic.

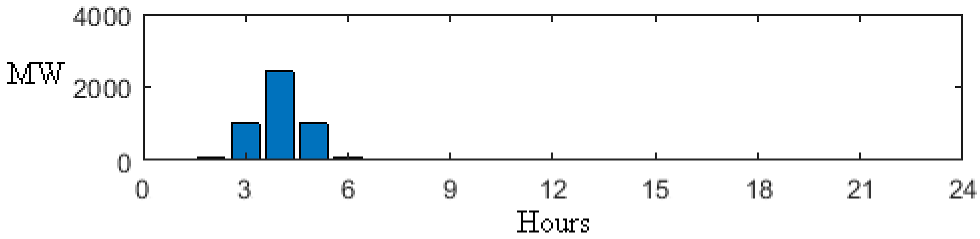

Figure 4.29: Impact of PEVs on the system demand - Smart charging - Aggressive.

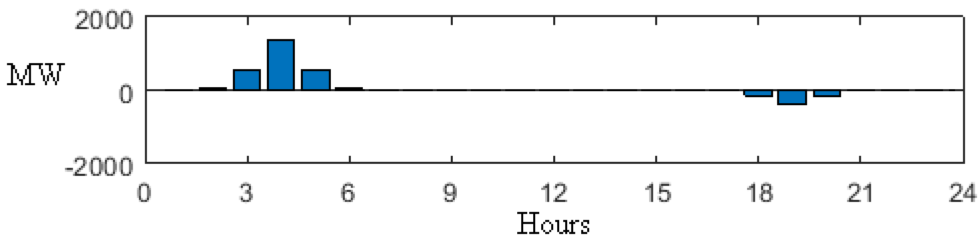

Figure 4.30: Impact of PEVs on the system demand - V2G - Likely.

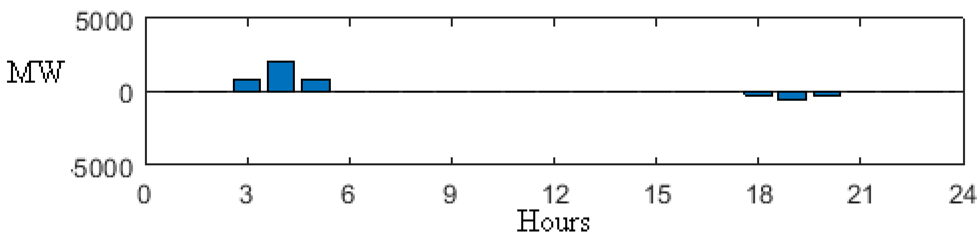

Figure 4.31: Impact of PEVs on the system demand - V2G - Optimistic.

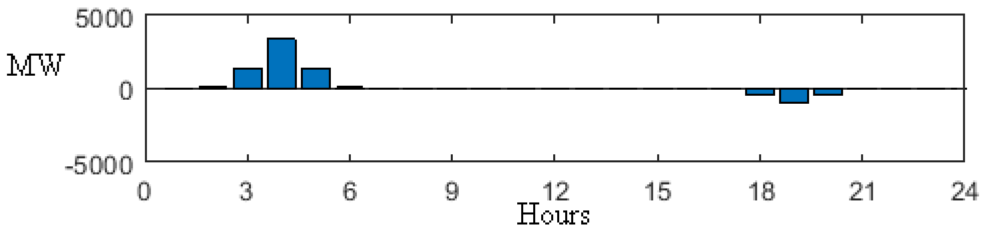

Figure 4.32: Impact of PEVs on the system demand - V2G - Aggressive.

Before running the expansion planning exercise for each scenario, it is still necessary to obtain the impact on the system demand for each scenario on an hourly basis for the entire planning horizon. For illustration of how the PEVs change the electricity demand, the impact of each scenario on the peak day of the original base case (without PEVs) in the 10th year is shown in Fig. 4.33. After getting the hourly demand, it is then obtained the annual peak demand along the 10-year horizon to be used in the TEP exercise.

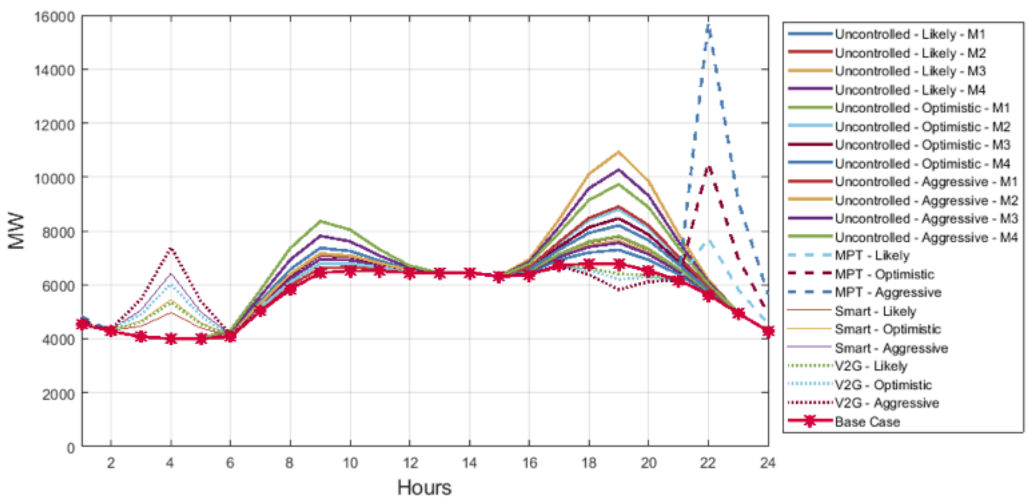

Figure 4.33: Impact of each PEVs scenario on the peak day in the 10th year.

The annual peak demand for each scenario is shown in Fig. 4.34. This figure also shows that in some scenarios the demand will exceed the generation capacity represented by the black dashed line. This indicates that a generation expansion planning (GEP) study should also be considered.

The TEP problem is conducted for each of the 21 scenarios under study and for the base case in which no PEVs were considered. For the Base Case the investment cost in new transmission equipment is 0.32 million USD and the global investment cost for each scenario is presented in Tables 4.4 and 4.5. It should be noticed that in some scenarios, TEP is not run because the demand in these scenarios cannot be met only with new transmission equipments since new generation units also have to be installed. These situations are indicated by the acronym GEP, indicating that a Generation Expansion Planning should be performed.

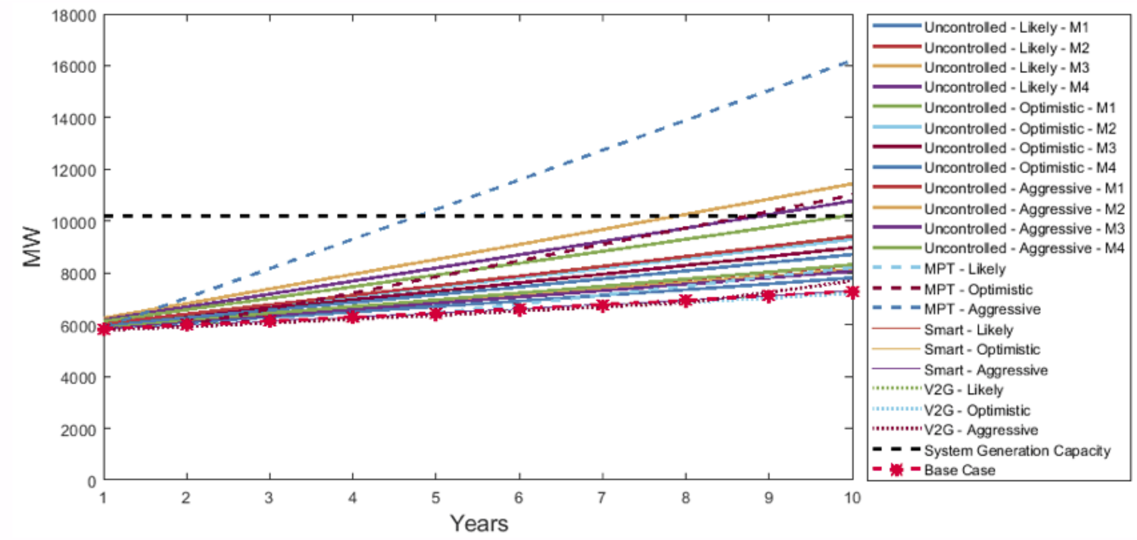

Figure 4.34: Peak demand for the different scenarios of PEVs (system generation capacity in black dashed line) along the planning horizon.

Table 4.4: Investment costs - Uncontrolled charging (Mi USD)

	Uncontrolled charging			
	M1	M2	M3	M4
Likely	0.5	0.91	0.93	0.99
Optimistic	1.13	1.35	1.60	2.12
Aggressive	1.31	GEP	GEP	GEP

Table 4.5: Investment costs - Multiple tariffs, smart charging and V2G (Mi USD)

	Multiple tariffs	Smart charging	V2G services
Likely	1.91	0.53	0.31
Optimistic	GEP	0.65	0.38
Aggressive	GEP	0.92	0.84

Finally, it is important to note from the results presented in Tables 4.4 and 4.5 that the multiple tariff scenarios presented the worst results since the electric car owners tend to start charging at the beginning of the low tariff period, on the other hand smart charging presented better results once the electric car charges are induced for off-peak periods. Finally, it is indicated that the best results were obtained with the V2G scenarios once besides inducing the loading to the off-peak periods, the V2G scenarios also offer electricity to the main grid at the peak periods. A thorough research still needs to be conducted with the V2G services mainly to verify which values should be paid to the PEVs owners since this type of service to the network decreases the life cycle of the EVs' batteries.

4.10 Conclusions

This chapter presents brief information on distributed energy resources and their impacts on the demand seen by the transmission network. In fact, distributed resources can affect the behavior of the demand and should be investigated in a more detailed way in order to evaluate its impact on the investment on new equipments in the transmission lines.

In this way, this chapter presents two simulations addressing this issue. The first simulation refers to the impact of solar distributed generation on the transmission expansion planning. The obtained results indicate that the penetration of solar distributed power generation can provide a better and safer operation for the system while reducing the operation costs, the transmission losses and the CO_2 emission level while contributing to diversify the generation mix. In this case the peak of injected solar DG is not coincident with the annual demand peak period which means that the annual peak demand seen by the transmission network remains unchanged. As a result, even if the injected solar DG is increased to 20% of the peak demand in each bus, the optimal expansion plan remains unchanged. This suggests that solar DG is not able in an isolated way to reduce the liquid demand seen by transmission networks and thus contribute to postpone transmission investments and reduce the corresponding cost. Therefore, as main conclusion of this simulation, solar DG should be associated to storage devices or demand response programs should be implemented in order to reduce the investment effort in transmission networks.

Finally, the second simulation was conducted in order to get the impact of the different scenarios of penetration and charging policies for electric vehicles on the transmission expansion planning. The TEP results reported in this simulation confirm that uncontrolled charging policy is likely to increase the peak demand and therefore requires more transmission investments over the years. The adoption of a multiple tariff scheme has a strong impact on the demand profile namely because there in practice a strong filling effect on the initial hours of the original valley period (that is, on the two or three hours immediately after 10 pm). As a result, this concentration effect originates a large increase of the required investments on the transmission system and in some cases the installed generation capacity is even unable to meet the new peak demand, as indicated in Table 4.5. Considering the required transmission investments, smart charging becomes an interesting option given that PEVs are charged when that is more adequate. However, if V2G is implementable given the required business models and communication infrastructures then we obtain the most reduced transmission investment costs, as indicated in Table 4.5. This is due to the fact that PEVs can now contribute to partially supply the demand using a portion of the energy stored in their batteries.

Chapter 5

Probabilistic transmission expansion planning

Forecasting is the art of saying what will happen, and then explaining why it didn't!

Anonymous (communicated by Balaji Rajagopalan)

5.1 Scope

This Chapter describes the theory and parameters often used to include probabilistic approaches in TEP problems as well as the developed formulation and the results of the tests that were performed using it.

Section 5.2 presents four different approaches to consider probabilistic planning criteria.

Section 5.3 fully describes the reliability indices used in TEP problems, while Section 5.4 addresses the reliability worth assessment.

Section 5.5 describes techniques to conduct adequacy evaluation studies in bulk power systems.

Section 5.6 details the probabilistic power generation models for wind, solar and hydro plants. Section 5.7 briefly describes the two main approaches used in large scale optimization problems involving uncertainties.

Section 5.8 describes a new approach and new contributions for the TEP problem based in the models and techniques described in previous sections.

The proposed approach is tested in Section 5.9 considering four simulations. The main conclusions about the Chapter and the performance of solution approaches are discussed in Section 5.10.

5.2 Probabilistic planning criteria

Power system outages very often originate reduction of profits for the intervening companies, interference in the emergency services and shut down of business supplied by electricity. This is the main reason that long term planning tasks should always consider reliability information and criteria due to events associated with the failures of equipment and due to the availability of renewable sources, as wind and PV. As an example of the mentioned costs, according to (House, 2013), between 20 and 55 billion USD are lost annually due storm-related outages in USA.

In this sense, the N-1 contingency criterion is widely used by the academia and power industry, although some probabilistic criteria can also be incorporated in the planning tasks. Therefore, four probabilistic approaches eventually included in TEP formulations are described in this section.

5.2.1 Probabilistic cost criteria

In this approach the costs associated with the energy not supplied are considered in the decision making regarding the commissioning of new equipments for the transmission network. The expected energy not supplied (EENS) results from faults or maintenance of equipments which in turn gives rise to interruptions.

The costs associated with these interruptions are usually referred in the literature as *unserved energy cost* or *unreliability costs*.

The unserved energy cost in a period p ($C_{ue,p}$) is obtained by estimating the EENS and multiplying it by the Value of Lost Load (VOLL, $/kWh) as present in Eq. (5.1). The VOLL can be interpreted as an estimated price that the consumers are willing to pay to avoid a service interruption.

$$C_{ue,p} = EENS_p.VOLL \tag{5.1}$$

The methods to estimate the VOLL are described in Subsection 5.4.1 and the methods to estimate the EENS are addressed in Subsection 5.5.2.

Therefore, once the EENS and VOLL are estimated, the unserved energy cost can be considered in the decision-making process. The decision-making is usually performed considering the investment costs, the operation cost of all GENCOs in the system and the mentioned unserved energy cost. However, the unserved energy cost can be incorporated in two different ways (Li, 2011) as follows:

i **Total cost method.**

In this approach the decision making uses the total cost of the system (C_{tot}), that is, the sum of investment (C_{inv}), operation (C_{op}) and unserved energy costs, as present in Eq. (5.2) in which κ is the present-worth value coefficient given by Eq. (5.3) and

d is the discount rate specified by the planner to the period under consideration;

$$C_{tot} = \sum_{p=1}^{np} (C_{inv,p} + C_{op,p} + C_{ue,p}).\kappa_p \tag{5.2}$$

$$\kappa_p = \frac{1}{(1+d)^p} \tag{5.3}$$

ii **Benefit/cost ratio method.**

In this method the investment, the operation and the unserved energy costs are estimated for each year in the planning horizon. The Benefit/Cost Ratio (BCR) is calculated for all the alternative plans, according to Eq. (5.4) and the decision making is conducted through the comparison of the corresponding BCR values. Thus, if the investment is considered as the cost, the reduction in operation and unserved energy costs are the associated benefits.

$$BCR = \frac{\sum_{p=1}^{np} (\Delta C_{op,p} + \Delta C_{ue,p}).\kappa_p}{\sum_{p=1}^{np} C_{inv,p}.\kappa_p} \tag{5.4}$$

According to Eq. (5.4), the larger BCR is, the better the candidate plan is, furthermore, an candidate plan with a $BCR < 1$ is not justified.

5.2.2 Specified reliability index target

In this approach, the annual reliability is considered a sub-problem of the main problem, which in turn usually optimizes investment and operating costs. Thus, given a candidate plan, the predefined indexes values of the reliability are calculated for the planning horizon and this plan is only considered feasible if, and only if, the calculated reliability value is higher than the predefined target reliability level. This approach was used in (Khodaei and Shahidehpour, 2013) and is shown in Fig. 5.1.

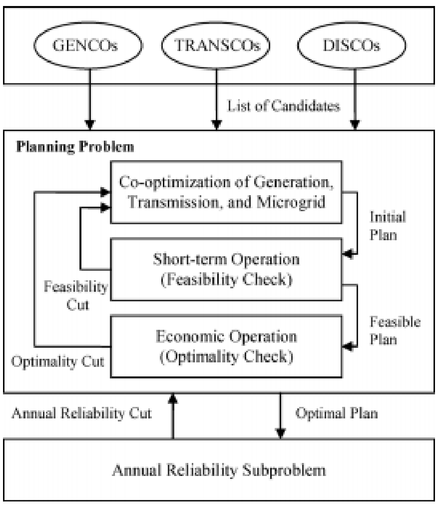

Figure 5.1: Specified reliability index target example, from (Khodaei and Shahidehpour, 2013).

The main problem in (Khodaei and Shahidehpour, 2013) was minimize the investment costs by generation companies ($GenCo$), transmission companies ($TransCo$) and distribution companies ($DisCo$), and operation costs. A reliability index is raised after a sub-optimal plan is found, and it is considered a secure solution if the reliability index is higher then the predefined one, otherwise, cuts are generated and added in the next iteration.

5.2.3 Relative comparison

In this approach the candidate plans are compared in relation to their reliability indices. Thus the decision criterion takes into account the different investment and reliability informations.

According to (Li, 2011) this approach generally leads to better solutions for the system, mainly because:

- The economic aspects related to the reliability index can also be compared;
- The historical of equipment failures/maintenance actions may change over the years and the reliability targets can transmit incorrect future performances;

5.2.4 Incremental reliability index

This approach is used when the unserved energy cost is difficult to perform because of a lack of equipment information, a lack of local interruption costs or even a due a huge computational effort.

Thus, the Incremental Reliability Index (IRI), which is basically the relationship between the improvement in the reliability and the investment costs of this improvement, as presented in Eq. (5.5). As can be noted, the option of ”do nothing” can not be considered as an investment. In thsi formulation, RI_B is the reliability index before the investment and RI_A is the reliability index after the investment.

$$IRI = \frac{RI_B - RI_A}{C_{inv}} \tag{5.5}$$

5.3 Reliability indices for TEP

There are two basic aspects that can be used to represent the reliability in power systems. In one hand the adequacy is related to the capacity of the system in supplying the electricity demand considering all the operational constraints. On the other hand, security is related to the capacity of the system to respond and hopefully survive to a disturbance occurred in a generation or transmission facility. Therefore, adequacy refers to a static vision of reliability while security is related with dynamic aspects.

In the next subsections, the reliability indices used in TEP studies are detailed.

5.3.1 Adequacy indices

The main adequacy indices used to estimate future reliability levels are (Li, 2011):

i **Probability of Load Curtailments (PLC)**

PLC is presented by Eq. (5.6) in which ρ_i is the probability of the system state i and Υ is the set of all system states with non zero value for the power not supplied;

$$PLC = \sum_{i \in \Upsilon} \rho_i \tag{5.6}$$

ii **Expected Frequency Load Curtailments (EFLC)**

EFLC is presented by Eq. (5.7) in which Fls_i is the frequency to move for a state i with non zero PNS and ft_i is the frequency of transition from a state with non zero PNS to other system state i also with non zero PNS;

$$EFLC = \sum_{i \in \Upsilon} (Fls_i - ft_i) \tag{5.7}$$

iii **Expected Duration of Load Curtailments (EDLC)**

EDLC is given by Eq. (5.8). In this expression T is the horizon in hours that is considered in the simulations;

$$EDLC = PLC.T \tag{5.8}$$

iv **Average Duration of Load Curtailments (ADLC)**

ADLC is given by Eq. (5.9) and is expressed in hours per outage;

$$ADLC = \frac{EDLC}{EFLC} = \frac{PLC.T}{EFLC} \tag{5.9}$$

v **Expected Power Not Supplied (EPNS)**

EPNS is given by Eq. (5.10) in which PNS_i represents the power not supplied in state i;

$$EPNS = \sum_{i \in \Upsilon} \rho_i.PNS_i \tag{5.10}$$

vi **Expected Energy Not Supplied (EENS)**

EENS is given by Eq. (5.11) in which D_i is the duration of state i.

$$EENS = \sum_{i \in \Upsilon} \rho_i.PNS_i.D_i \tag{5.11}$$

The adequacy indices mentioned in this subsection are defined for the entire system. However, as suggested in (Li, 2011), they can also be formulated for individual buses.

5.3.2 Reliability worth indices

Although it is very difficult to measure the reliability worth in a direct way, it is common to consider the reliability cost as a surrogate. (Li, 2011) present two important indices for reliability worth evaluation as follows:

i **Expected Damage Cost(EDC)**

The EDC is given by Eq. (5.12) , in which $W(D_i)$ is the customer damage function. This function expresses in USD/year how each customer would be harmed if he suffered a power outage involving the power not supplied for a given duration. This function typically depends on the duration of the interruption in the sense that several consumers might be little harmed for short duration interruptions while this impact would increase if this duration increases;

$$EDC = \sum_{i \in \Upsilon} PNS_i.Fls_i.W(D_i) \tag{5.12}$$

ii **Value of Lost Load (VOLL)**

VOLL is expressed in USD/kWh and is given by Eq. (5.13).

$$VOLL = \frac{EDC}{EENS} \tag{5.13}$$

5.3.3 Security indices

As security is related with the dynamic part of reliability, that is, to the ability of the system to respond to a disturbance, the security indices take into account the stability of the system when a contingency happens.

In fact, when any type of contingency happens, the system may remain stable or become unstable eventually resulting in blackouts, for example. Thus, some sort of the so-called *remedial-action schemes* (RASs) should be adopted in order to ensure that the system remains in the stable state or that it is able to regain stability. RASs must be selected and adopted in time and can even include load shedding as a way to regain the stability of the system. According to (Li, 2011), the most common security indexes, are:

i **Probability of System Instability (PSI)**

PSI is given by Eq. (5.14) in which Φ is the set of all system instability states and ρ_i is the probability of system instability state i.

$$PSI = \sum_{i \in \Phi} \rho_i \tag{5.14}$$

ii **Risk Index (RI)**

RI is defined by Eq. (5.15) in which Φ' is the set of all system states with contingencies (unstable and stable system states) and R_i is the response to the contingency that can be, for instance, a load shedding.

$$RI = \sum_{i \in \Phi'} \rho_i . R_i \tag{5.15}$$

5.4 Reliability worth assessment

5.4.1 Value of Lost Load (VOLL)

According to (Li, 2011), there are four methods to estimate the VOLL:

i **Method based on Customer Damage Functions, CDFs.**

The method returns an average customer-specific social damage as result of electricity supply interruptions. The techniques used to build these functions are addressed in Subsection 5.4.2;

ii **Method based on capital investments.**

Generally, building or installing new equipments on the network lead to an improvement of the reliability. Accordingly, this method uses the ratio of the investment cost in new equipments (USD/year) regarding the respective improvement in reliability (MWh/year);

iii **Method based on Gross Domestic Product (GDP).**

This method uses the relation between the GDP (USD) of a region and its energy consumption (MWh).

iv **Method based on revenue lost to a utility due to power outages.**

This method uses the electricity tariff (kWh) as the VOLL.

5.4.2 Customer Damage Functions (CDFs)

Building CDF functions can be conducted under three approaches as follows based on customer surveys:

- Contingent valuation approach: a value of energy interruption is obtained based on the values that customers accept to pay to avoid it;
- Direct cost approach: from questionnaire responses, the impact and costs related to outages scenarios are identified;
- Indirect cost approach: from user experiences obtained by questionnaire responses, the costs related to outage situations are calculated.

According to (Li, 2011) the establishment of CDF functions includes the steps detailed in Fig. 5.2.

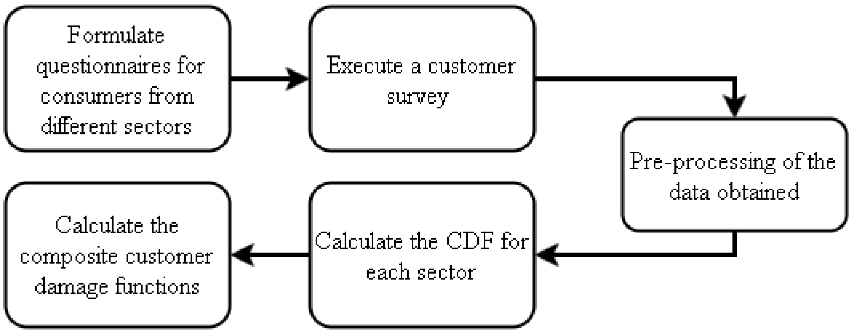

Figure 5.2: Steps to establish a CDF.

Based on (Li, 2011), Tables 5.1 and 5.1 provide examples about the CDF values obtained in USD/kW and USD/kWh respectively. The CDFs were based on a composite sample of 52.36% of residential consumers, 17.61% of commercial consumers and 30.03% of industrial consumers. The "unknown mix" refers to unknown customer sectors and their CDF is different from the composite CDF. Additional information about the statistical data can be obtained in the mentioned reference. Note that commercial consumers have the highest damage costs and the residential consumers the smallest ones.

Table 5.1: CDF in $/kW, from (Li, 2011)

Duration (min)	Residential	Commercial	Industrial	Unknown Mix	Composite
0-19	0.20	11.40	5.50	1.90	3.76
20-59	0.60	26.40	8.60	4.00	7.55
60-119	2.80	40.10	19.60	8.50	14.41
120-239	5.00	72.60	33.60	15.10	25.49
240-480	7.20	147.60	52.10	26.50	45.41

Table 5.2: CDF in $/kWh, from (Li, 2011)

Duration (min)	Residential	Commercial	Industrial	Unknown Mix	Composite
10	1.20	68.40	33.00	11.40	22.58
40	0.90	39.60	12.90	6.00	11.32
90	1.90	26.70	13.10	5.70	9.63
180	1.70	24.20	11.20	5.00	8.52
360	1.20	24.60	8.60	4.40	7.54
Average	1.38	36.70	15.76	6.50	11.92

5.4.3 Applications for reliability worth assessment

Reliability is a very important aspect to take into account in the expansion planning exercises as it was mentioned in Subsection 5.2.1. Additionally, it is important to recognize that reliability aspects and the investment and/or operation costs are conflicting functions in the sense that improving some reliability index typically requires increasing investment or operation costs. Obviously, to overcome some possible faults on the system and activate some *remedial-action schemes*, for instance, the network must be prepared namely having some degree of equipment redundancy together with more advanced technology which increases the investment costs.

On the other hand, the damage cost for consumers, related to supply interruptions, generally decreases as the reliability level associated to the service increases as it is illustrated in Fig. 5.3.

The optimal target level of reliability can be achieved when the total cost presents the lowest value. This point is termed as *system reliability* in Fig. 5.4.3.

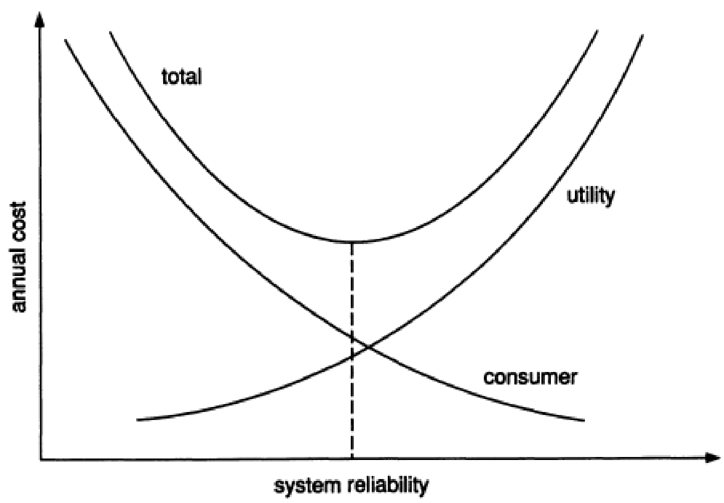

Figure 5.3: Sytsem costs as functions of reliability, from (Li et al., 2013).

5.5 Composite system adequacy evaluation

In the assessment of power systems reliability, there are two different approaches that allow evaluating the adequacy of a power system and that can be used in TEP formulations: deterministic and probabilistic approaches. Deterministic criteria are based on a pre specified rule that is defined considering the experience obtained through the analyses of other power systems. In TEP, the N-1 deterministic criterion to consider single equipment failures is often taken in account. In some systems, more demanding reliability criteria as the N-2 or the N-1 plus a short list of second order contingencies can also be considered or specified in the grid codes, obviously requiring extra investments and more redundancy to be meet.

However, this approach does not consider the stochastic behavior of power systems in the sense that all contingencies are considered at the same level while, in fact, some of them may produce more severe consequences and some of them are certainly more probable than others. This means that in order to consider uncertainties related to power systems such as the failure of system components and the probability of occurrence of such events, the weather conditions or the demand growth, a stochastic model should be used instead.

Regarding the probabilistic approaches, there are two main families of methods that should be mentioned: the analytical and the simulation ones. The calculation of system reliability indices is the main goal of both approaches. However, the application of pure analytical methods to complex power systems is not adequate due to the number of simplifications and assumptions that usually need to be accepted. This is the main reason that turned the simulation approaches, as the Monte Carlo Simulation, very popular to internalize a number of aspects that are typical of the behavior of power system equipments.

5.5.1 Component outage models

The equipments considered to model component outages are transmission lines, transformer, cables, capacitors, reactors and generation units.

Markov processes are the well-known reference that allow treating different system states. Fig. 5.4 shows a typical two-state Markov model in which the up state represents the equipment operating in perfect conditions and the down state represents the equipments under failure (outage). The failure and repair rates, λ and μ, are modelled by exponential distributions. In other words, these distributions model the duration of the system events.

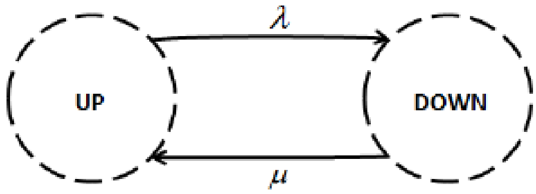

Figure 5.4: Markov model composed by two states, where λ is the failure rate and μ is the repair rate.

The failure and repair rates can be used to obtain the unavailability of an equipment according to Eq. (5.16). Assuming that $MTTR$ is the mean time to repair and it corresponds to the inverse of the repair rate, and that $MTTF$ is the mean time to failure and that it corresponds to the inverse of the failure rate, then the unavailability U can also be obtained using $MTTR$ and $MTTF$. Finally, if f_{af} is the average failure frequency in failures per year, then the unavailability can also be obtained using f_{af} and $MTTR$.

$$U = \frac{\lambda}{\lambda + \mu} = \frac{MTTR}{MTTF + MTTR} = \frac{f_{af} * MTTR}{8760} \tag{5.16}$$

5.5.2 Methods for adequacy evaluation

The calculation of reliability indices consists of the evaluation of the expected value of a function Fs, according to Eq. (5.17) in which x is a vector representing the state of all bulk system components, X is the set of all possible system states, $Fs(x)$ is the value of the function to evaluate the adequacy of the system for the state x and $\rho(x)$ is the probability of the state x.

$$E(Fs) = \sum_{x \in X} Fs(x).\rho(x) \tag{5.17}$$

The adequacy evaluation can be performed by state enumeration or simulation techniques.

The state enumeration takes all the states x of the system to calculate Eq. (5.17) in an exact way. However, this is an exhaustive approach being impractical for real systems, even admitting that each component only resides in two states, the up and the down states indicated in Fig. 5.4. On the other hand, the simulation processes, commonly known as Monte Carlo Simulations (MCS), use a random sampling of states in order to estimate the reliability indices.

According to (Li et al., 2013), MCS has strong advantages over analytically methods, some of them are highlighted below:

- the systems effects such as reservoir operating conditions and weather conditions, can be included in MCS;
- the number of samples that it is required to analyse is independent of the size of the system;
- MCS can simulate probability distributions of failure and restoration of system components;

MCS estimates $E(Fs)$ according to Eq. (5.18). In this expression N_x is the number of states sampled from the set X and x_j is a state vector from this sample.

$$E^{'}(Fs) = \frac{1}{N_x}.\sum_{j=1}^{N_x} Fs(x_j) \tag{5.18}$$

The variance of F_s can be obtained by Eq.(5.19).

$$V(F_s) = \frac{1}{N_x - 1}.\sum_{j=1}^{N_x} (F_s(x_j) - E^{'}(F_s))^2 \tag{5.19}$$

The coefficient of variation β_V measures the quality of the estimated value after sampling and analysing a sample of N_x states, according to Eq.(5.20).

$$\beta_V = \frac{\sqrt{V(F_s)}}{\sqrt{N_x}.E^{'}(F_s)} \tag{5.20}$$

The β_V parameter can be used to control the convergence of the MCS simulations. After specifying a target value for β_V, this parameter is calculated as the simulation progresses which means updating the values of the expected value and of the variance of F_s

to be used in Eq. (5.20). As soon as the calculated value of β_V becomes smaller than the specified one, the simulation ends indicating that estimation of the expected value is now sufficiently stable.

There are two different types of MCS approaches: the chronological and the non-chronological. When the TEP approach uses the EENS, for instance, to characterize the system reliability, it is important to keep track of the sequence of states determining the life of the system together with the duration of each of these states. This means that in these cases a chronological version of the MCS should be used.

The non-chronological and chronological versions of the MCS are described below. More information about these approaches can be obtained in (Braga, 2004) and (da Silva, 2014).

- **Non-chronological MCS**

Consider a bulk power system constituted by n_{eq} equipments (transmission lines, transformers, cables, capacitors, reactors and generation units). For each equipment x_{eq1}, x_{eq2}, ..., $x_{eqn_{eq}}$ let us admit that the respective probability of failure ρ_{eq1}, ρ_{eq2}, ..., $\rho_{eqn_{eq}}$ is known. Additionally, let us admit that it is available a function that generates uniformly random numbers n_{udr} ranging from 0 to 1.

Step 1: For each equipment x_{eqi} of the system (i=1,...,n_{eq}) sample a random number n_{udr};

if $n_{udr} < \rho_{eqi}$, then the equipment is in the failure state;

otherwise the equipment is in service.

Step 2: Evaluate the state x_j using $F_s(x_j)$;

Step 3: For $j = 1, ..., N_x$ use Eq. (5.18), (5.19) and (5.20) to update the estimate of the values of the expected value, of the variance and of the β_V parameter;

Step 4: Check the convergence of the algorithm using the pre-specified target value for β_V. Let us call this pre specified value as β_V^{stop}. Then, if $\beta_V \leq \beta_V^{stop}$ the algorithm converges towards a estimate of $E(F_s)$, otherwise a new iteration begins in step 1.

- **Chronological MCS**

Consider a bulk power system constituted by n_{eq} equipments (transmission lines, transformers, cables, capacitors, reactors and generation units). For each equipment x_{eq1}, x_{eq2}, ..., $x_{eqn_{eq}}$ let us admit that the respective failure rate λ_{eq1}, λ_{eq2}, ..., $\lambda_{eqn_{eq}}$ and repair rate μ_{eq1}, μ_{eq2}, ..., $\mu_{eqn_{eq}}$ are known. Let us also admit that it is available a function that generates uniformly distributed random number n_{udr} ranging from 0 to 1. Finally, let us consider that in the initial state all equipments in the system are entirely available, that is, all of them are in the up state.

Step 1: For each equipment in operation sample a random number n_{udr} and determine the operating time (or time to fail) using Eq. (5.21). For each equipment in the failure state sample a random number n_{udr} and determine the repair time using Eq. (5.22).

$$t_{f_i} = -\frac{1}{\lambda_{eq_i}}.ln(n_{udr}) \tag{5.21}$$

$$t_{r_i} = -\frac{1}{\mu_{eq_i}}.ln(n_{udr}) \tag{5.22}$$

Step 2: Check which equipment has the shortest time t_x (operation or repair times);

Step 3: Evaluate the state x_j using $F_s(x_j)$. In this state, there is a number of equipments that are in the up state while some others are in the failure state thus being under repair. If F_s represents the power not supplied, and the planner wants to estimate the EENS, then the value of $F_s(x_j)$ should be multiplied by the shortest time t_x to obtain the new contribution to the EENS;

Step 4: If $t_x = t_{f_i}$ then, the corresponding equipment reached the failure state and a repair time must be calculated using Eq. (5.22). If $t_x = t_{r_i}$ then, the corresponding equipment reached the end of the repair state and a time to failure must be calculated using Eq. (5.21). The chronology of the system must be updated with this failure or repair states and the total simulation time T_t must be incremented by t_x;

Step 5: If the total simulation time t_x reaches a pre-specified value (8760 hours for instance) or if $\beta_V \leq \beta_V^{stop}$ the algorithm converges towards an estimate of $E(F_s)$,otherwise a new iteration begins in step 1.

5.6 Probabilistic power generation models

As the power generation coming from intermittent, non controllable and low predictable renewable sources is increasing in recent years, it is important to incorporate their intrinsic features in long-term expansion studies because the mentioned intermittent nature can influence the optimal solution plan (Munoz et al., 2012).

In this sense, solar and wind power generation are certainly the most auspicious technologies, since, in one hand, solar has become the world's popular new type of electricity generation with almost 73 GW added during 2016, while about 55 GW of wind power capacity was added during the same period. On the other hand, the wind installed capacity reached 487 GW in 2016 while solar installed capacity reached 303 GW (Sawin et al., 2013).

In the next subsections we present and discuss probabilistic models to consider the impact of renewable generation in long term transmission expansion planning models.

5.6.1 Wind uncertainty and power generation models

The wind speed has a direct impact in the wind generation and it is very often represented in the literature by the Weibull distribution as in (Rathore and Roy, 2016), (Hetzer et al., 2008) and (Kayal and Chanda, 2015). Fig. 5.5 presents an example of this similarity using synthetic data.

The Weibull PDF W_{pdf} is modelled by Eq. (5.23), in which f_{sh} is the shape factor given by Eq. (5.24), f_c is the scale factor calculated by Eq. (5.25), u is the wind speed,

τ represents the Gamma function, μ_u is the average value for the wind speed in the study time and σ_u is the standard deviation.

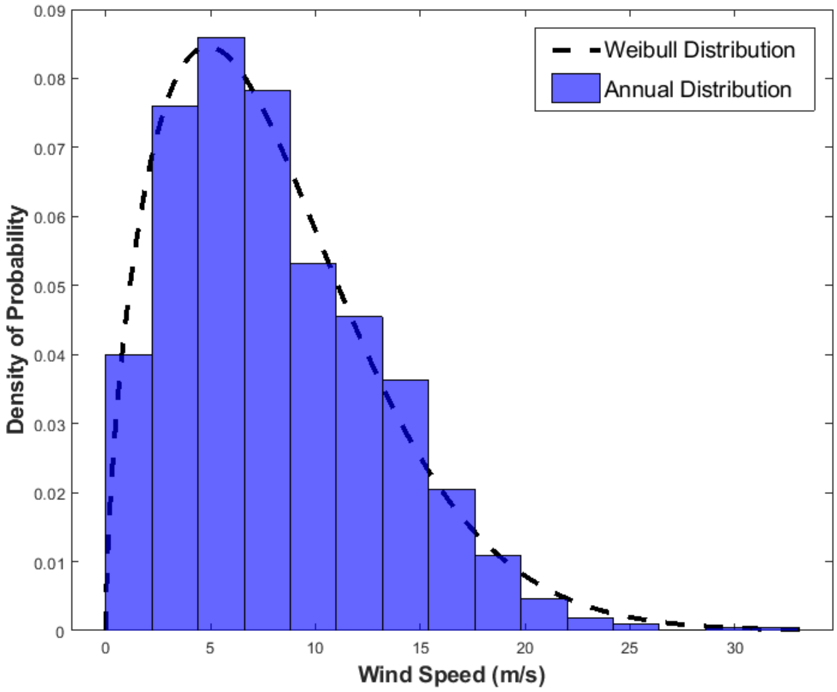

Figure 5.5: Distribution of wind speed.

$$W_{pdf} = \frac{f_{sh}}{f_c}.\left(\frac{u}{f_c}\right)^{f_{sh}-1}.e^{-\left(\frac{u}{f_c}\right)^{f_{sh}-1}}, \forall f_c > 1, f_{sh} > 0 \tag{5.23}$$

$$f_{sh} = \left(\frac{\sigma_u}{\mu_u}\right)^{-1.086} \tag{5.24}$$

$$f_c = \frac{\mu_u}{\tau(1 + 1/f_{sh})} \tag{5.25}$$

Therefore, the output power of a wind turbine (Pwt) depends on the wind speed according to Eq. (5.26) and represented by Fig. 5.6, where Per is the rated wind power, u_c, u_r and u_f are the cut-in, rated and cut-out wind speeds.

$$Pwt(u) = \begin{cases} 0, if\ u < u_c \lor u > u_f \\ Per.\left(\frac{u-u_c}{u_r-u_c}\right), if\ u_c \leq u \leq u_r \\ Per,\ if\ u_r \leq u \leq u_f \end{cases} \tag{5.26}$$

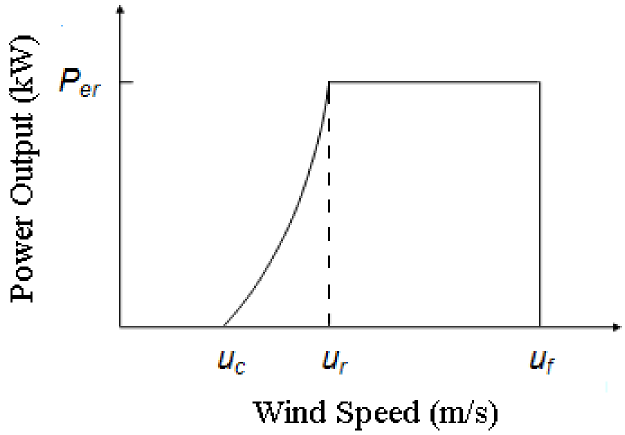

Figure 5.6: Power output of a wind turbine.

5.6.2 Solar uncertainty and power generation models

Solar photovoltaic generation is directly influenced by local solar irradiance and it is generally addressed in the literature following the Beta PDF as in (Atwa et al., 2010) and (Kayal and Chanda, 2015). The Beta PDF, B_{pdf} , is presented by Eq. (5.27) in which the shape parameters f_{sh1} and f_{sh2} are given by Eq. (5.28) and Eq. (5.29), s is the solar irradiance, μ_s is the average solar irradiance and σ_s is the standard deviation.

$$B_{pdf} = \frac{\tau(f_{sh1} + f_{sh2})}{\tau(f_{sh1}).\tau(f_{sh2})}.s^{f_{sh1}-1}.(1-s)^{f_{sh2}-1}, \forall\, f_{sh1} > 0 \,\wedge f_{sh2} > 0 \tag{5.27}$$

$$f_{sh1} = \frac{\mu_s.f_{sh2}}{1-\mu_s} \tag{5.28}$$

$$f_{sh2} = (1-\mu_s).\left(\frac{\mu_s(1+\mu_s)}{\sigma_s} - 1\right) \tag{5.29}$$

Following the approach detailed in (Kayal and Chanda, 2015), the output power of a solar plant (Psp) is given by Eq. (5.30), in which $Nmod$ is the number of solar panels, Ig and Vg are the current and voltage characteristics of a PV module given by Eq. (5.31) and Eq. (5.32) respectively and FF is the fill factor given by Eq. (5.34). In Eq. (5.31) to (5.34) I_{sc} is the short circuit current, k_c is the current temperature coefficient, T_{cg} is the cell temperature, V_{oc} is the open circuit voltage, k_v is the voltage temperature coefficient, T_A is the ambient temperature, Not is the nominal operating temperature and I_{MPP} and V_{MPP} is the current and voltage at maximum power point, respectively.

$$Psp(s) = N_{mod}.I_g.V_g.FF \tag{5.30}$$

$$I_g = s(I_{sc} + k_c.(T_{cg} - 25)) \tag{5.31}$$

$$V_g = V_{oc} - k_v.T_{cg} \tag{5.32}$$

$$T_{cg} = T_A + s.\frac{Not - 20}{V_{oc}.I_{sc}} \tag{5.33}$$

$$FF = \frac{V_{MPP}.I_{MPP}}{V_{oc}.I_{sc}} \tag{5.34}$$

5.6.3 Hydro uncertainty and power generation models

The hydrological conditions and the electricity market schedules can directly affect the output of a hydro plant. Additionally, this output can also be affected by the intermittent nature of other sources as wind and solar power plants in the sense that the variation of the outputs of these intermittent units will have to be compensated for instance by hydro units.

Moreover, the different types of hydro plants originate different typical operation strategies. In fact, reservoir hydroelectric plants have the benefit of being dispatchable, although the future level of stored water depends on the dispatch in previous periods and on the expected inflows, which also incorporates a considerable uncertainty degree.

The run-of-river hydroelectric plants use the energy flowing naturally from a river elevation and this water flow is directly used to generate electricity since the capacity to store water is usually very reduced. Of course, its output power is totally dependent of the water inflow which can be affected by uncertainty.

Finally, the pump-hydro-storage units are able to be dispatched as a reservoir hydroelectric plant and can also operate as a storage unit, pumping the water from a lower reservoir to a higher level one. This type of operation mode can be associated to a strategy to profit from differences on the electricity prices between different periods of the day or due to an excess of renewable generation coming from wind or solar plants that can be used to pump water that will be used later (Castronuovo and Lopes, 2004).

Power systems with high shares of hydro installed capacity are commonly characterized by a transmission-intensive nature in order to deal with climatic phenomena which, for example, can determine dry conditions in one region while there are large rainfalls in another one. Thus, the grid must be robust to deal with different export/import patterns among regions and to accommodate several economic dispatches.

As proposed in (Gomes and Saraiva, 2017a) it is possible to deal with the mentioned hydro uncertainties in the planning exercises considering different hydro shares in the system from different generator patterns, as shown in the Fig. 5.7, considering the share of hydro generation in the supply of the demand. Departing from an hydro share in the starting year, this model considers a number of scenarios that develop along the planning period so that, in this case, a total of 30 scenarios for the evolution of the hydro share are built. In this approach an expansion planning solution is considered feasible if it ensures that the system operates properly, that is, with zero PNS, for all the hydro scenarios, or on a part of them if the approach admits some risk of deficit, that is, if one admits that in some scenarios the supply of the demand is not completely ensured.

Another way of considering hydro uncertainties is to consider historical inflow series for each hydro generator or subsystem along an extended period of time in order to adequately capture the associated long-term uncertainties in several years. Thus, generation scenarios can be drawn using the mean and the standard deviation of the probability distribution used to model these series.

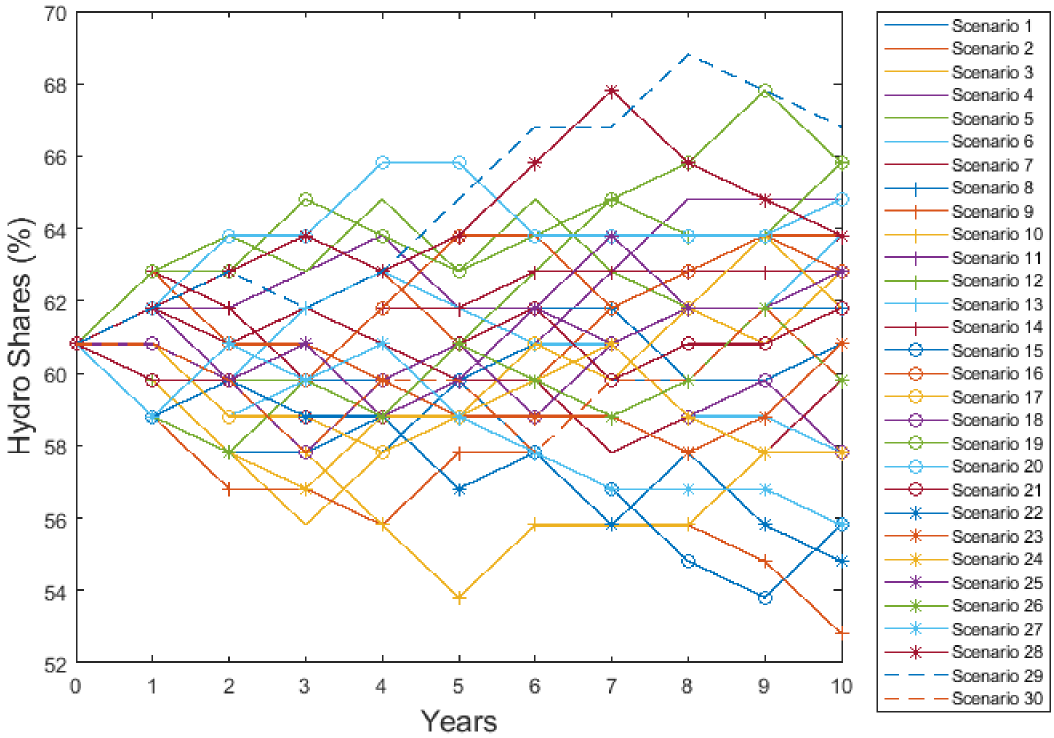

Figure 5.7: Hydro share generation scenarios.

5.7 Optimization under uncertainty

In the last years, the methods that were more frequently used to deal with uncertainties in optimization studies include stochastic programming and robust optimization. In the next two subsections these concepts will be briefly presented.

5.7.1 Stochastic programming

Stochastic programming is an efficient approach to solve problems involving random variables mainly due to the stages known as *here and now* and *wait and see*. In general, the variables of the first-stage are the decision variables of the optimization problem, and are determined before considering the variables affected by uncertainties and modeled in a random way. This corresponds to the *here and now* stage. Therefore, after considering these uncertainties, corrective actions are taken with the purpose of adapting the decisions selected in the first stage taking into account the second stage variables. This step corresponds to the *wait and see* stage.

The scenarios used in stochastic programming are generated based on a certain probability distribution of the uncertain data. Formulations of the TEP problem using stochastic programming are described in (Carrión et al., 2007), (Akbari et al., 2011) and (Alaee et al., 2016) and are usually conducted considering two types of decisions:

i Network expansion decisions made by the planner;

ii Network operation decisions made by the system operator.

The decisions of the system operator depend, somehow, on the decisions taken by the network planner in the expansion step, that is, the system operator will adopt decisions based on market laws, renewable generation forecasts and electrical demand, for instance, but shall also take into account the physical installations and equipments available in the network.

On the other hand, the network expansion decisions of the planner must take into account the future conditions of the system in a way that the available equipments allow the system operator to safely operate the system.

As the future operating conditions are uncertain, using the stochastic programming approach the network expansion decisions are identified in a first stage (*here and now*) and, after considering uncertainties affecting the random variables, the previous decisions are tested and eventually changed or adapted in the second stage (*wait and see*).

The first stage variables are the equipment candidates for expansion and the second stage variables are the variables that are typical in optimal power flow problems such as generation, load shedding, etc.

Accordingly, the objective of the two-stage stochastic programming in TEP problems is to identify first-stage solution plans that allow a safe operation of the system considering all possible realizations of the random variables that are admitted in the second stage.

The impact of the solution plans obtained by stochastic programming in TEP problems can be measured by the Value of Perfect Information (VPI) and by the Value of the Stochastic Solution (VSS), as detailed below.

- **Value of perfect information (VPI)**

  It is a parameter that reflects the value that planners should pay to obtain perfect forecasts about future system conditions. It can be obtained from the solution of the TEP problem in each scenario as if it was a deterministic problem, that is, treating the information as perfect. Thus, at the end of the expansion planning runs, the average of the cost savings for each planning is calculated by comparing each of them with the solution obtained by the stochastic programming;

- **Value of the stochastic solution (VSS)**

It is a parameter that represents the benefits of adopting stochastic programming in TEP problems involving uncertainties. It can be obtained by treating the problem as if it was deterministic (substituting the random variables by the corresponding mean value, for example). Thus, at the end of the planning, the deterministic solution is tested against the scenarios considered in the stochastic programming in order to obtain the values of adjustments of the second stage (*wait and see*) and to obtain the average for each scenario. The VSS is the difference between the average of the objective functions obtained by the deterministic approach after the adjustments and the value of the objective function of the solution obtained by stochastic programming.

5.7.2 Robust optimization

Stochastic programming is a very efficient optimization method involving uncertainties that can be handled with probability distributions. However, non-random or epistemic uncertainties are too difficult, or even impossible in some cases, to be modeled by probability distributions.

Robust optimization is an excellent alternative to deal with this type of uncertainty and it is considered as an easy-to-implement method. In this method the uncertainties are described by parametric sets, which are related to an infinite number of scenarios (Chen et al., 2014). Thus, the uncertainties can be treated using information about lower and upper bounds of the uncertain non-random variables.

In general, the uncertain variables are fixed at the worst-case values, and thus, the values obtained in the robust optimization are conservative in relation to the uncertainty scenarios that are inherent to this approach.

At this point, three observations can be highlighted:

i Setting uncertain variables at their upper or lower bounds is a much simpler approach than building probability distributions for them;

ii Conservative solutions related to several uncertainty scenarios are extremely important in TEP problems due to the costs associated with reliability. Additionally, there is a typical conservative behavior of system operators or of network expansion planners which means that such an approach adapts well to this type of reasoning;

iii The conservativeness nature of solutions yielded from robust optimization can be adjusted by changing the uncertainty sets.

The criteria adopted to conduct robust optimization include *minmax cost* and *minmax regreat* that were applied in (Chen et al., 2014). These criteria use the worst case scenario paradigm in the optimization problem. However, they select the worst case in different manners.

The *minmax cost* takes the scenario related to the highest cost as worst case. On the other hand *minmax regreat* takes the scenario that leads to the highest regret for the decision maker as the worst case.

5.8 Proposed Stochastic TEP Model

The main motivation of the developed stochastic planning model is to propose, formulate and test a novel and more comprehensive mathematical model that considers a number of issues that have been addressed separately in some cases or that were not yet incorporated in TEP models. These issues include:

i the uncertainties intrinsic to wind-solar-hydrothermal systems, as well as those related to the electricity demand and with the life cycle of generation and transmission equipments;

ii a reliable system able to meet not only the deterministic N-1 contingency criterion but also probabilistic events of equipment failure over the planning horizon;

iii a real-world approach ensuring the holistic view through the dynamic year-by-year representation of the investment decisions and the true grid behavior adopting the AC-OPF model;

iv a robust solution plan able to deal with different hydrological conditions and with the intermittence, non-controllability and low-predictability of solar and wind energy resources when the system is under high electricity demand and low renewable generation.

Thus, the proposed approach aims at assessing the impact of the robust solution plan in the system costs, while enabling analyzing the impact of different decision-criteria used in the TEP literature. More specifically, the research questions that the present work seeks to answer are:

i How does the system reliability behave by adopting a degree of robustness in the planning problem when the system is under high electricity demand and low non-hydro renewable generation?

ii How does the decision-making criterion adopted in the planning substantially influence the total cost of the system?

As a way to answer these questions, the present methodology incorporates two new contributions considering what is currently available in the literature:

i A new worst case parameter is proposed in order to ensure that the system is sufficiently robust to overcome conditions with high electricity demand and low non-hydrological renewable energy;

ii A broad comparison and a detailed analysis of the most common decision-making models adopted in the TEP literature and their impact on the system total cost when neglected.

TEP models usually consider the peak load, which is associated to the worst-case scenario, to quantify the investment requirements. When using this approach, the planner admits that the solution plans obtained with this consideration ensure a safe operation of the system in normal conditions (no perturbations, contingencies, etc) for any other electricity demand value in any time of the planning horizon.

However, the worst-case scenario only based on the peak load may not be enough to ensure a proper operation of the system in normal conditions. Scenarios having high electricity demand (however lower than the peak value) and low non-hydro renewable generation are not taken into account in this simplistic approach. Therefore, we introduce the concept of **net peak** to consider these situations.

The **net load** is the difference between the hourly electricity demand and the corresponding hourly non-hydro renewable generation, in this case solar and wind. The **net peak** corresponds to the highest value of the **net load**. Fig. 5.8 illustrates these concepts for a day.

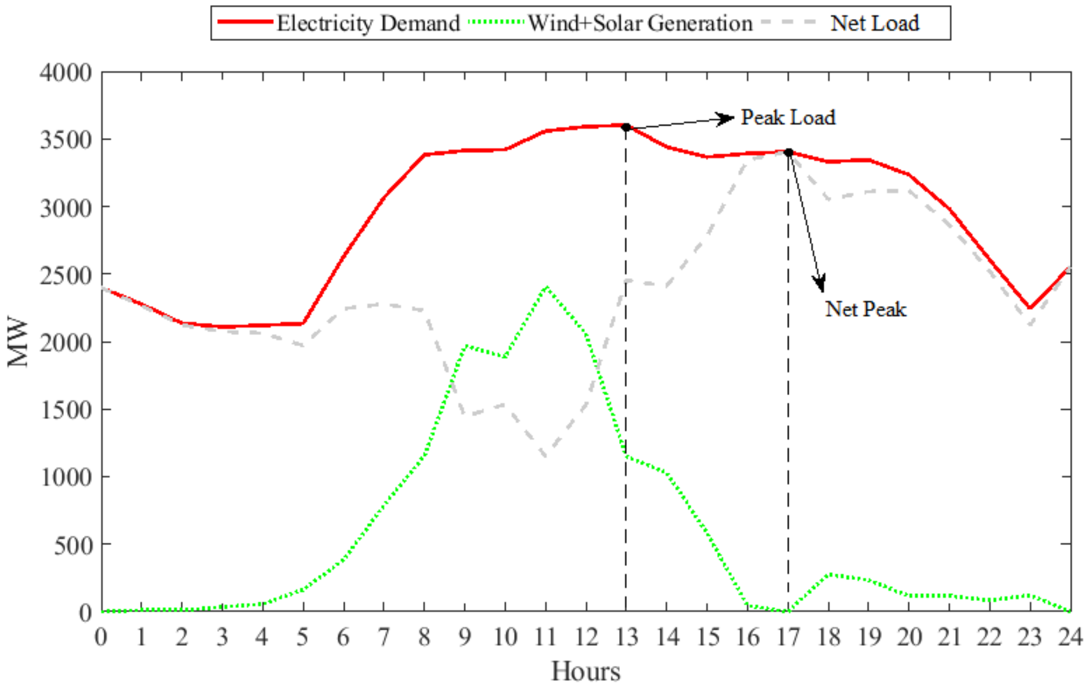

Figure 5.8: Net load and net peak.

Therefore, the proposed approach takes as worst case the set containing the annual peak load and a set of net peaks for each season of each year over entire planning horizon. Besides, nsc equiprobable scenarios are considered for each net peak identified. These scenarios are built as follows:

i Generate hourly profiles of renewable generation and electricity demand for the entire planning horizon. In this first step, consider the random variables (wind generation, solar generation, demand) substituted by their average values;

ii Identify the peak load (with the corresponding time) for each year and the net peaks for each season (with the corresponding time) for the entire planning horizon;

iii For each net peak, with their corresponding time, generate nsc scenarios of renewable generation and electricity demand considering the probability distributions assumed for each random variable.

Thus, in this approach, a candidate alternative will be tested against the peak load and the several net peak scenarios representing high electricity demand and low renewable non hydro generation.

Although the objective function is formulated considering the probabilistic cost criterion under the total system cost approach presented in Subsection 5.2.1 and using Eq. (5.2) and Eq. (5.3), checking the N-1 condition is very time consuming. As a result, the proposed stochastic model could take too long to check this condition for all alternative solutions. Therefore, a feasibility check algorithm is used to select feasible alternative solutions and to reduce the computational effort. In this way, for each solution it is checked in the first place if the system operates with zero PNS admitting that all components are in operation. If non zero PNS values are obtained in this initial step, then a penalty factor is applied and no further N-1 check is done. If zero PNS is obtained, then the N-1 single contingencies are tested as shown in Fig. 5.9. If non zero PNS values are obtained for some of these contingencies, a penalization factor is also applied.

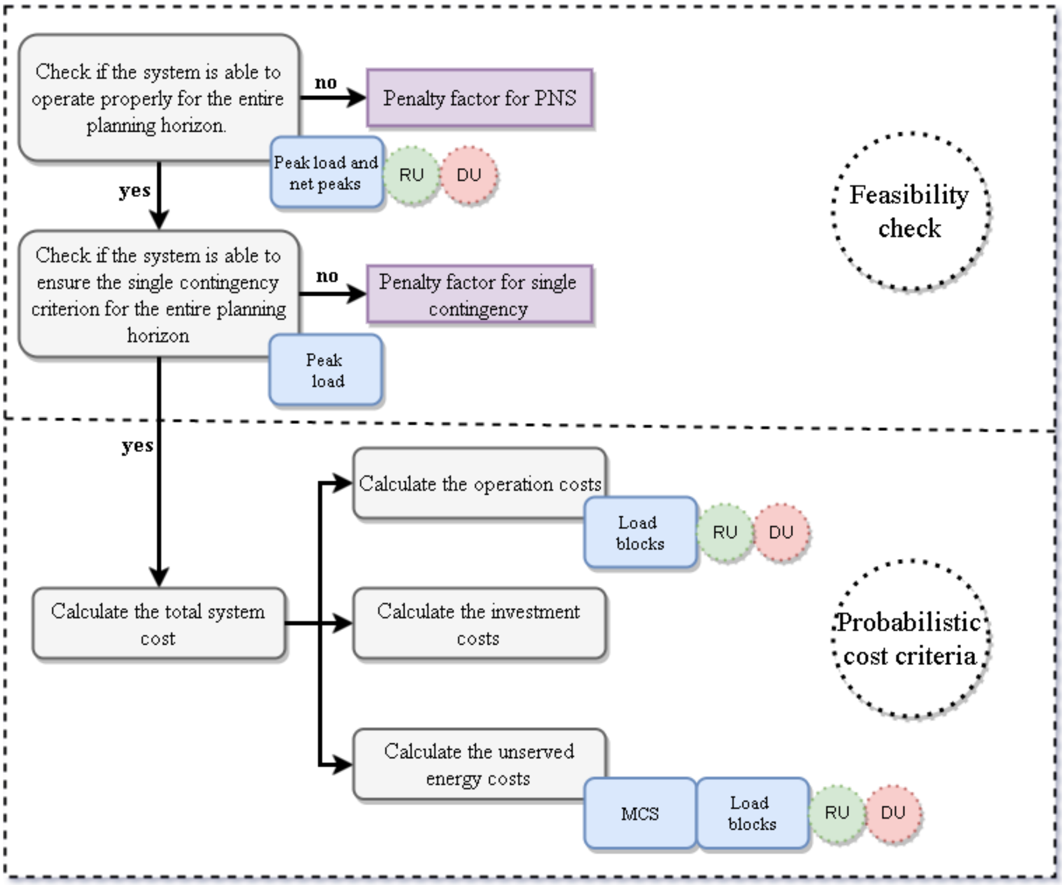

Figure 5.9: Proposed methodology. RU stands for renewable uncertainties and DU for demand uncertainties.

Therefore, for each alternative solution, the feasibility check is performed before the probabilistic cost criteria and the proposed methodology follows the three steps described below.

i First of all, is checked if the system is able to operate properly (zero PNS) for the entire planning horizon considering the peak and the net peak demand, if positive go to step ii, if not the alternative solution has the objective function equals to a penalty factor for PNS, that is, $PNS.\beta_1 + \beta_2$. Note that this step considers the renewable and demand uncertainties (RU and DU in Fig. 5.9) through the net peak scenarios;

ii The contingency criterion is checked, if the alternative solution is able to ensure the N-1 criterion go to step iii, if not it has the objective function equals to a penalization factor for single contingency, that is, $N_{cont}.\beta_2$, in which N_{cont} is the number of equipments that cannot meet the single contingency condition;

iii The alternative solution belongs to the set of feasible solutions and its objective function is the system total cost composed by investment, operation and unserved energy costs and given by Eq. (5.2). Note that the operation cost takes into account the renewable and demand uncertainties through the load blocks and the unreliability cost is obtained using Monte Carlo Simulation considering the same load blocks.

Regarding the different terms in Eq. (5.2), that is, the investment, the operation and the unserved energy costs, they are calculated as follows.

- **Investment cost ($C_{inv,p}$)**

The investment cost in new equipments for the transmission grid is given by Eq. (5.35) in which the equipment cost in a period p, $C_{eq,p}$, is defined in Eq. (5.36) taking into account the capital cost Cap_{eq} of each equipment. According to Eq. (5.37) and (5.38), once a candidate equipment is installed, its investment state δ (initiated as $\delta = 0$) will be set at '1' for the remaining years, while respecting the commissioning time T_{eq}^{com} (Khodaei and Shahidehpour, 2013).

$$C_{inv,p} = \sum_{eq=1}^{neq} C_{eq,p} \tag{5.35}$$

$$C_{eq,p} = Cap_{eq}.(\delta_{eq,p} - \delta_{eq,p-1}) \tag{5.36}$$

$$\delta_{eq,p} = 0, \forall eq \in \Omega^{ce} \ \wedge \forall p < T_{eq}^{com} \tag{5.37}$$

$$\delta_{eq,p-1} \leq \delta_{eq,p}, \forall eq \in \Omega^{ce} \wedge \ \forall p \tag{5.38}$$

- **Operation cost ($C_{op,p}$)**

The operation cost represents all costs paid by the system operator to GENCOs due the electricity generation. It includes terms related with thermal plants, wind farms, solar and hydro power plants. Several load blocks are considered into the operational costs as a way to get an adequate trade-off between accuracy and computational time as in (Khodaei and Shahidehpour, 2013) in terms of the representation of the demand along each year.

The load blocks used in this approach refer to the average load in each season of the year. In a similar way, the renewable energy used in these blocks represent the average generation over the seasons. In order to compute this cost it is solved an AC-OPF problem in the first place using the formulation in Section 3.2.1. In this problem we consider the operation costs of thermal units and zero costs for the wind and solar units so that these technologies have priority in the dispatch.

Once this problem is solved, the total operation cost is evaluated using (4.39) that considers the cost associated to the dispatched thermal units given by plus payments that eventually have to assigned to wind and solar units.

The first term of Eq. (5.39) represents the operational cost of a thermal power plant expressed as the sum of a quadratic function presented by Eq. (5.40).

The second term of Eq. (5.39) is the payment to assign to a wind farm given by Eq. (5.41). In this formulation, the system operator pays a direct value $\psi_{1,wd}$ for the wind GENCOs depending on the wind generation (Rathore and Roy, 2016). On the other hand, this formulation also considers a penalty term $\psi_{2,wd}$ when the system operator does not use all the available wind power (Hetzer et al., 2008).

Finally, the last term of the Eq. (5.39) represents the payment to assign to solar power plant owners that is presented by Eq. (5.42). The direct and the penalty costs used in this equation are similar to the ones used for wind farms.

$$C_{op,p} = \sum_{lb=1}^{nlb}(\sum_{ter=1}^{nter} C_{ter,lb,p}(P_{G,ter,lb,p}) + \sum_{wd=1}^{nwd} C_{wd,lb,p}(P_{G,wd,lb,p}) + \sum_{sol=1}^{nsol} C_{sol,lb,p}(P_{G,sol,lb,p})) \tag{5.39}$$

$$C_{ter,lb,p}(P_{G,ter,lb,p}) = \varepsilon_1.P^2_{G,ter,lb,p} + \varepsilon_2.P_{G,ter,lb,p} + \varepsilon_3 \tag{5.40}$$

$$C_{wd,lb,p}(P_{G,wd,lb,p}) = \psi_{1,wd}.P_{G,wd,lb,p} + \psi_{2,wd}(P^{av}_{wd,lb,p} - P_{G,wd,lb,p}) \tag{5.41}$$

$$C_{sol,lb,p}(P_{G,sol,lb,p})) = \psi_{1,sol}.P_{G,sol,lb,p} + \psi_{2,sol}(P^{av}_{sol,lb,p} - P_{G,sol,lb,p}) \tag{5.42}$$

- **Unserved energy cost ($C_{ue,p}$)**

The unserved energy cost is obtained by estimating the EENS and multiplying it by the Value of Lost Load (VOLL), which corresponds to the estimated value that the consumers are willing to pay to avoid a service interruption. Note that VOLL is an input to the proposed model, whereas EENS is obtained by using a non-chronological Monte Carlo simulation to randomly generate states, in which some equipment can be in the failure state.

The probability metrics based state reduction method developed in (Wu et al., 2007) is used to reduce the number of states to be analysed. Although it corresponds to a non-chronological sampling, each sampled state is tested using a load block regarding which the duration is defined. As a result, the Energy Not Supplied (ENS) associated to each analysed state is estimated by the product of the PNS by the duration of the associated load block. These ENS values are weighted by the state probability to estimate the EENS. The unserved energy cost is finally given by Eq. (5.43) and (5.44).

$$C_{ue,p} = VOLL.EENS_p \tag{5.43}$$

$$EENS_p = \sum_{lb=1}^{nlb} \sum_{sa=1}^{nsa} \rho_{sa}.\Delta t_{lb,p}.PNS_{sa,lb,p} \tag{5.44}$$

5.9 Numerical simulations

This section presents the results obtained by the application of the proposed stochastic TEP model over a modified version of the IEEE 118-bus system. The system has 118 buses, 54 generators and 186 branches, the installed capacity is 9966 MW and the peak demand is 6363 MW in the initial period. The original data for this IEEE test system is provided in Appendix A.0.2 and the changes introduced in the course of this research are provided below. The list of candidate equipments is obtained by applying the Security CHA presented in Section 3.6 and is given in Table 5.3 so as to enable the perfect replication of the simulations by any researcher interested in doing so. The renewable hydro generator plants, wind farms and solar power plants are installed according to Table 5.4. Data “Share” correspond to percentage values regarding the installed capacity.

Table 5.3: Equipments considered for expansion

List of candidate equipment
n_{6-7}, n_{8-30}, n_{8-30}, n_{8-5}, n_{12-117}, n_{30-38}, n_{30-38}, n_{35-36}, n_{37-39}, n_{47-69}, n_{49-51}, n_{51-58}, n_{54-56}, n_{54-56}, n_{54-56}, n_{55-56}, n_{60-61}, n_{63-59}, n_{63-64}, n_{64-65}, n_{68-116}, n_{70-71}, n_{70-71}, n_{76-77}, n_{77-78}, n_{77-78}, n_{77-78}, n_{77-78}, n_{77-78}, n_{82-83}, $n_{106-107}$, $n_{106-107}$, $n_{106-107}$, $n_{106-107}$, $n_{106-107}$, $n_{106-107}$, $n_{106-107}$, $n_{106-107}$, $n_{106-107}$, $n_{110-112}$, $n_{110-111}$

Table 5.4: Renewable generation mix

Generation	Buses	Share	Total (MW)
Hydro	10, 26, 46, 100	14.40%	1435 MW
Solar	103, 104, 105, 107, 110, 111, 112, 113, 116	9.79%	976 MW
Wind	4, 6, 18, 19, 49, 59, 61, 74, 76, 77	15.24%	1519 MW

The average and standard deviation per season of the wind speed and solar radiation are taken from (Kayal and Chanda, 2015), whereas the data for the hydro output power are taken from U.S. Energy Information Administration (www.eia.gov), that contains data for 45 years. The deterministic values for the electricity demand given in Appendix A.0.2 are used as the average values of the corresponding probability distributions while the standard deviation is set at 5% of the corresponding average value. The hydro output data for each season is provided in Table 5.5 and these values are given in % of the maximum capacity.

Table 5.5: Conventional hydroelectric power output

Winter		Spring		Summer		Autumn	
μ_h	σ_h	μ_h	σ_h	μ_h	σ_h	μ_h	σ_h
70.35%	7.94%	73.81%	10.17%	79.08%	9.93%	59.52%	6.22%

Regarding the wind turbine and PV module specifications, the used data is provided in Table 5.6 and these values were taken from (Kayal and Chanda, 2015).

Table 5.6: Wind turbine and PV module specifications

Atribute	Value
Cut-in-speed	3m/s
Rated wind speed	12 m/s
Cut-out speed	25 m/s
Current at maximum power point	7.76 A
Current temperature coefficient	0.00545 A/°C
Nominal cell operating temperature	43°C
Open circuit voltage	36.96 V
Short circuit current	8.38 A
Voltage at maximum power point	28.36 V
Voltage temperature coefficient	0.1278 V/°C

The planning parameters used in the simulations are presented in Table 5.7. The direct costs of wind $\psi_{1,wd}$ and solar $\psi_{1,sol}$ generation are considered the same, as well as their underestimation costs ψ_2. This data is taken from (Khodaei and Shahidehpour, 2013). VOLL is obtained from (Khodaei and Shahidehpour, 2013) and the penalization factors β_1 and β_2 were set so that feasible expansion plans, that is, plans with zero PNS and that ensure that the system operates with zero PNS under N-1 contingencies, always have total system cost lower than non-feasible solutions. The value for the operation cost parameters of each thermal generator, ε, were obtained from case118 system available in (Zimmerman et al., 2011) and the annual demand growth, called demand factor, is set at 1.05%. Finally, the horizon has 10 years and the VOLL was set at 10 USD/MWh.

Table 5.7: Planning parameters

d	5% per year	β_1	10^{13}
ψ_1	10 USD/MWh	β_2	10^{11}
ψ_2	6 USD/MWh	VOLL	10 USD/MWh
np	10 years	nsc	5

Regarding the parameters used in the EPSO algorithm adopted to solve the TEP problem, all simulations were performed using 20 particles in the population, a replication parameter (r) equals to 3 and the stop criterion corresponds to run 20 consecutive iterations with the same $gbest$.

In the simulations, load blocks representing the demand in the seasons of the year are used in order to get insight about the operational costs and the unreliability costs. The load blocks provide the average values of the electricity demand and the respective time periods in hours. These values are calculated over the hourly behavior of the electricity demand available in Appendix A.0.1. The data for the load blocks regarding the initial year are provided in Table 5.8 For the subsequent years of the planning horizon the demand factor mentioned above is applied.

Table 5.8: Load blocks data for the first year of the planning

	Winter	Spring	Summer	Autumn
Average demand (MW)	4263.21	3563.28	4072.32	3563.28
Duration (h)	2856	1536	2184	2184

Regarding the scenarios of net peaks, as the electric demand grows linearly over the years of the horizon and the generation mix does not change, it is only necessary to identify the time of the net peaks for the first year and then apply the demand factor and the uncertainty model over the remaining years. Table 5.9 provides the information about the net peaks for the first year of the planning horizon.

Table 5.9: Net peaks in the first year

	Winter	Spring	Summer	Autumn
Electricity demand (MW)	5959.54	5160.18	5700.93	5244.05
Non-hydro renewable generation (MW)	497	51	144	5
Time	Day 353 at 16h	Day 108 at 20h	Day 136 at 17h	Day 226 at 20h

All the simulations were conducted using the EPSO tool described in Subsection 3.5.3 and considering the single contingency N-1 criterion on an Intel i7 with 16 GB RAM and clock at 3.4 GHz. Additionally, it was used parallel computing to reduce the computation time. In order to answer the research questions that were formulated in the beginning of Section 5.8, we will now present results for Case Studies that will be characterized below. Therefore, considering the respective results, it is possible to analyse how the different decision-making criteria adopted in the TEP literature can influence the system total cost and how the net peak scenarios impact on the system reliability.

- **Case 1**

  TEP is performed by only considering the peak load and the investment cost as the decision-criterion, which is a common approach in the TEP literature and can be found in (Mendonça et al., 2016) and in (De Mendonça et al., 2014). Although the decision is taken only considering the investment in new equipments, the operational cost and the unreliability costs are calculated to compare against other cases. Besides, the behavior of the solution plan is tested against the net peak scenarios in order to verify if it is robust enough to accommodate the associated uncertainties;

- **Case 2**

  TEP is performed by only considering the peak load and using the sum of the investment and the operational costs as the objective function to be minimized. This case corresponds to the most common approach used in TEP literature and can be found in (Moradi et al., 2016). In this case, the unreliability and risk costs are also calculated, as in Case 1, in order to compare against other cases. As in Case 1, the behavior of the solution plan is tested against the net peak scenarios in order to verify if it is robust enough to deal with the associated uncertainties;

- **Case 3**

  TEP is conducted by only considering the peak load and using the sum of investment, operational and unreliability costs as the decision-criterion, although this is an unusual approach. The study conducted by (Khodaei and Shahidehpour, 2013) indicates that the unreliability cost should be incorporated in the planning tasks. As in Cases 1 and 2, the behavior of the solution plan is tested against the net peak scenarios in order to verify if it is robust enough to deal the associated uncertainties;

- **Case 4 - Proposed approach**

  TEP is conducted by considering the peak load and the net peak scenarios using the sum of investment, operational and unreliability costs as the decision-criterion and this corresponds to the complete formulation developed in the course of this research.

Accordingly, the results obtained for all simulations are presented in Table 5.10. The shadow cells in this table indicate the elements that were used as decision criteria in each Case according to the description of the Cases provided above. A direct analysis of the first three sets of results (Cases 1, 2 and 3) indicates that as decision criterion gets more complete, that is, as one moves from Case 1 to Case 3, the system total cost gets reduced. This result is explained considering that there is a slight increase in the investment cost in new equipment associated with a significant decrease in the operation and unserved energy costs. This suggests that a small increase in investment costs is more than overshadowed by the reductions in operation and reliability costs, thus indicating that the adoption of more comprehensive formulations enable obtaining important advantages along the planning horizon.

According to the results, Case 1 was not able to meet 30% of the net peak scenarios, Cases 2 and 3 were not able to meet 20% of them, while the proposed risk-based TEP was able to meet all net peak scenarios. It is important to note that Cases 1, 2 and 3 transmit to the planner the illusion that the system can meet all different demand values just because it can meet the peak load ("worse case"). However, this proves not to be true because there a significant number of net peak scenarios for which the obtained expansion plans do not ensure supplying the associated demand.

Therefore, only the proposed stochastic TEP approach is able to ensure that the system operates properly, that is with zero PNS, under low renewable generation and high electricity demand. These results are displayed in Table 5.11.

Table 5.10: Results of the case studies - (The decision criterion of each case is in gray)

Case study	Investment cost (Bi USD)	Operation cost (Bi USD)	Reliability cost (Bi USD)	Total cost (Bi USD)
Case 1	0.3972	19.124	0.2179	19.7391
Case 2	0.5171	18.496	0.3046	19.3177
Case 3	0.5124	18.527	0.2477	19.2871
Case 4	3.0598	18.654	0.1251	21.8389

Table 5.11: PNS in net peak scenarios

	Net peak scenario with PNS
Case 1	30%
Case 2	20%
Case 3	20%
Case 4	0%

Case 1 takes 45 iterations to be solved over 8.4 hours, Case 2 converges in 139 iterations in about 48.97 hours, Case 3 uses 47 iterations and it requires 26.39 hours while Cases 4 takes 91 iterations and 104.25 hours. The relative computational effort is 11.24 minutes/iteration, 21.14 minutes/iteration, 33.69 minutes/iteration and 68.73 minutes/iteration for Cases 1, 2, 3 and 4 respectively. These results reflect the complexity of adopting more complete models for the TEP problem, that is, as the model gets more robust and complete, the larger the computational effort required.

The equipments selected and included in the final expansion plan in each Case are provided by Table 5.12 below.

Table 5.12: Solution of each case study

Simulation	Solution plan
Case 1	Year 1: n_{76-77}, $n_{110-112}$, n_{68-116}, n_{12-117}, n_{77-78}. Year 10: n_{8-30}
Case 2	Year 1: n_{76-77}, $n_{110-112}$, n_{68-116}, n_{12-117}, n_{77-78}, n_{8-30}, n_{30-38}, n_{30-38}.
Case 3	Year 1: n_{76-77}, $n_{110-112}$, n_{68-116}, n_{12-117}, n_{77-78}, n_{30-38}. Year 2: n_{8-30}, n_{30-38}
Case 4	Year 1: n_{64-65}, n_{76-77}, n_{77-78}, $n_{110-112}$, n_{68-116}, n_{12-117}, $n_{106-107}$, n_{35-36}, $n_{106-107}$, n_{80-83}, $n_{106-107}$, $n_{110-111}$, $n_{106-107}$, n_{8-5}, n_{30-38}, n_{77-78}, n_{63-59}, n_{47-69}, n_{49-51}, n_{54-56}, n_{37-39}, n_{77-78}, n_{70-71}, $n_{106-107}$, n_{70-71}, $n_{106-107}$, n_{70-71}. Year 3: n_{55-56}. Year 6: $n_{106-107}$. Year 8: n_{54-56}

As it can be seen, as more complete and comprehensive is the analysis, more equipments are added to the system and, consequently, more expensive is the plan. This is line with the increase of the investment cost when moving from Case 1 to Case 4 already indicated in Table 5.10.

5.10 Conclusions

This chapter provides several information about the probabilistic approach developed to solve the TEP problems. The formulations include a new stochastic parameter, called net peak, for TEP problems that include generation systems with renewable energy sources. The uncertainties related with the wind speed, the hydrological conditions, the solar irradiation, the equipment availability and the electricity demand are fully modelled and internalized in the model.

Furthermore, the planning holistic view over the entire planning horizon and the true grid behavior of an AC grid are considered by the year-by-year representation of the investment decisions and the adoption of the full AC Optimal Power Flow model. The proposed approach was solved by the evolutionary EPSO algorithm and considers as decision criterion the system total cost composed by the investment, the operation and the unserved energy costs. The well-known and standard TSO N-1 contingency criterion was also considered in the proposed approach.

TEP models usually take the electricity demand as deterministic parameter, that is, the system should evolve over time in order to meet the load. In these models, the forecasted peak demand is used as a standard case which means that if the system is able to meet the peak load, it is assumed that it can meet any other electricity demand pattern. The results obtained in this chapter showed that this conclusion is not always true in systems with renewable generation (note that the system used in the simulations has a renewable penetration considered moderate). In fact, the net peak must also be taken into account and, according to the results, neglecting this information can result in underestimating the investment in new equipment and, even worse, can originate non zero power not supplied. Furthermore, the transmission expansion planning exercise also leads to insufficient plans when the operation or unserved energy costs are not considered. Therefore, it is important to use comprehensive TEP formulations, as the one formulated along this research, so that more robust and better quality expansion plans are obtained.

Chapter 6

Multiobjective transmission expansion planning

> It is not greedy to enjoy a good dinner, any more than it is to enjoy a good concert. But I do think there is something greedy about trying to enjoy the dinner and the concert at the same time.
>
> *Gilbert K. Chesterton*

6.1 Scope

This chapter provides insights about multiobjective optimization problems and how transmission expansion planning can be handled considering several conflicting objectives eventually associated to different stakeholders.

In this context, Section 6.2 addresses the basic concepts of multiobjective optimization and Pareto multiobjective approach. Classical and intelligent methods used to solve multiobjective problems are briefly presented in Section 6.3.

The multiobjective tools NSGA-II and MEPSO are widely used and have consolidated results in the literature regarding the TEP problem. These tools are described in Section 6.4.

A number of indices to evaluate the performance of multiobjective tools are presented in Section 6.5.

Section 6.6 describes the novel MEPSO-II algorithm developed in scope of this research and Section 6.7 presents the results of the numerical simulations conducted to solve a multiobjective TEP problem and a broad comparison against the results obtained using the NSGA-II and the MEPSO.

The main conclusions about these results are provided and discussed in Section 6.8.

6.2 Basic concepts on multiobjective optimization

6.2.1 Multiobjective optimization problem

Modelling real problems namely the ones involving some sort of optimization procedure typically requires some level of abstraction in order to identify decision variables, relations among them, limitations on the available resources and drivers conducting the search for the solution. This abstraction step leads to the formulation of an optimization problem typically including decision variables, constraints and objectives.

In real life, we rarely face a single objective to optimize. In fact, real optimization problems frequently include different objectives that the decision-maker would like to attain hopefully in a simultaneous way. However, these objectives typically display a contradictory nature so that if each objective was considered at a time over the same set of constraints, the optimal solutions would be different. In these cases, a set of trade-offs between these objectives provide the decision-maker a more complete set of information to allow him taking more sounded decisions.

Therefore, in multiobjective problems, the term "optimal solution" loses its well-known meaning from single-objective problems. In fact, when considering more than one objective, the solution provided in the optimization process should include a set of trade-offs between these objectives and the decision-maker will use this information to choose in a more informed way which solution better fits his criteria.

To illustrate these concepts let us consider, for instance, a problem in which two objective functions (OF_1 and OF_2) have to be minimized. Now, take the candidate solutions x, y and z displayed in Fig. 6.1. If we have to decide what is the best solution between x and y which one would be the best choice? In one hand $OF_1(y)$ is smaller than $OF_1(x)$, on the other hand $OF_2(x)$ is smaller than $OF_2(y)$. Therefore the decision-maker needs a multi criteria analysis to choose a solution between x and y. However, if now we have to decide which is the best solution between y and z, the decision is easier once $OF_1(y)$ is smaller than $OF_1(z)$ and $OF_2(y)$ is also smaller than $OF_2(z)$.

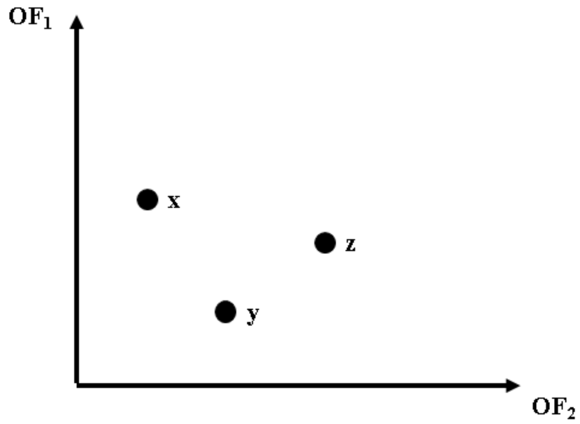

Figure 6.1: An example of solutions in a multiobjective problem.

The whole theoretical development of this chapter will evolve from this simple analysis. The set of trade-offs delivered to the decision-maker should incorporate solutions similar to the solutions x and y, that is, solutions that are better in at least one criterion but worse in at least one other.

In the example of Fig. 6.1, solutions x and y are known as *non-dominated solutions*, and the solution z is known as a *dominated solution*. The next subsection will develop these concepts.

It is commonplace for optimization problems in power systems the consideration of multiple objectives. In fact, these multiple objectives are, very often, conflicting ones. For instance, in TEP problems the planner can consider the minimization of the investment in new equipments on the grid while considering the maximization of the system reliability. The system operator must consider, very often, multiobjective problems taking into account environmental issues, economic load dispatch, system losses, etc. For this reason, tools that are able to incorporate this multiple objective nature of several real problems have been receiving an increasing attention by the scientific community in the last years.

Regarding the TEP problems, several objectives can be addressed at the same time, as presented in Section 2.10. Accordingly, the general formulation of the multiobjective TEP problem with n objectives is similar to that presented in Section 2.2 and is given by Eq. (6.1) to Eq. (6.4).

$$Minimize/Maximize \ (OF_1, OF_2, ..., OF_n) \tag{6.1}$$

Subject to:

$$Physical \ Constraints \tag{6.2}$$

$$Financial \ Constraints \tag{6.3}$$

$$Quality \ of \ Services \ Constraints \tag{6.4}$$

As mentioned in Section 2.2, physical constraints are associated to the generator and branch capacity limits, financial constraints refer to the maximum amount that is available to be invested in a certain period and the quality of service constraints are for instance related with the maximum value allowed for power not supplied in normal or contingency regimes or to limit values specified for reliability indexes.

The decision variables, attributes, criteria, objectives and goals of the multiobjective TEP problem have the same definition of that presented for the single objective TEP problem in Section 2.2.

6.2.2 Pareto multiobjective optimization

Consider again the optimization problem with two objectives (minimization of OF_1 and OF_2) from the previous section. Let us also consider again the solutions x, y and z

from Fig. 6.1. As mentioned, selecting a final solution between x and y is not immediate to do because in one hand $OF_2(x)$ is smaller than $OF_2(y)$ and, on the other hand, $OF_1(y)$ is smaller than $OF_1(x)$. Therefore, the decision-maker should adopt a multi-criteria framework in order to choose one of them. However, when choosing between the solutions y and z, y is the best option because y has more reduced values than z both for OF_1 and OF_2. In this context, x and y are termed as non dominated solutions while z is a dominated solution.

In general, assuming a problem with n objectives to be minimized, one solution y dominates another solution z if y improves at least the value of one of the objectives and it does not degrade the value of any of the other, as it is translated by Eq. (6.5).

$$y \prec z \leftrightarrow \exists i \mid OF_i(y) < OF_i(z) \wedge \nexists j \mid OF_j(z) < OF_j(y), i, j \in (1, 2, ..., n), y \neq z \tag{6.5}$$

if we now get back to example in Fig. 6.2, considering the objectives OF_1 and OF_2 to be minimized, the points in the gray area are dominated by y because for every point in this area the values of both OF_1 and OF_2 are larger than the values of the objective functions for y.

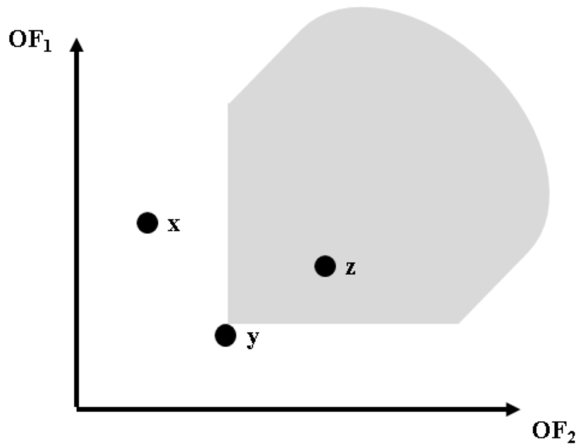

Figure 6.2: Steps to establish a CDF.

The set of non-dominated solutions is known as *Pareto-Front*. In Fig. 6.3, the dashed line represents the Pareto-Front for a bi-objective problem. In general, as mentioned in (Coello et al., 2007), it is not simple to find an analytical formula for the Pareto-Front and in fact, in most cases, it is impossible to characterize it in an analytical way. The usual procedure to build the Pareto-Front is to compute a number of solutions with the respective objective function values and, when there is a sufficient number of them, it is then possible to analyse all these solutions and to classify them as non-dominated or dominated solutions and, consequently, build the Pareto-Front (PF_{true}).

According to (Cohon, 2004) the consideration of multiple objectives in defining planning strategies can provide improvements in the decision-making process as:

i A large spectrum of alternatives is often identified when a multiobjective approach is employed;

ii Multiobjective approaches can provide more suitable roles for the participants in the planning and decision-making tasks;

iii Multiobjective approaches also provide a more realistic model of a problem.

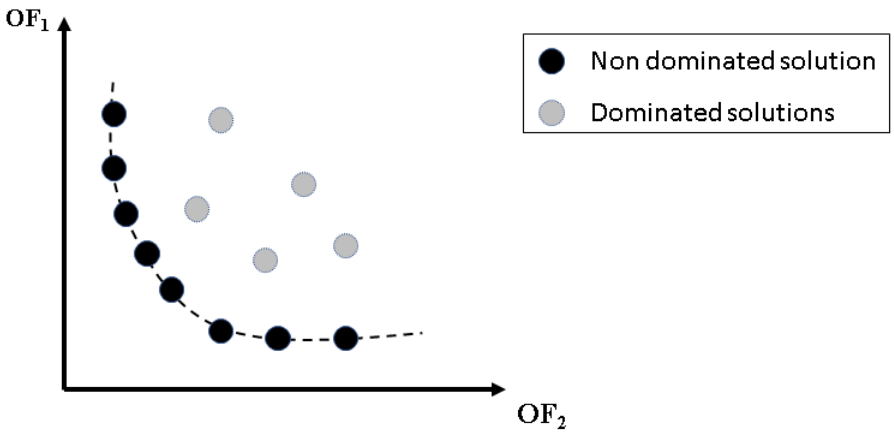

Figure 6.3: Pareto-Front representation.

6.3 Multiobjective solution approaches

The approaches and techniques for the solution of multiobjective problems have been developed over the years so that the different techniques that are employed can be categorized chronologically, according to (Lee and El-Sharkawi, 2008), as classic approaches and intelligent methods.

Classical approaches basically consist of converting the multiobjective problem into a single objective one and are usually driven by mathematical programming. On the other hand, the intelligent methods only gained relevance after the development of metaheuristics and the increase of the processing power of the computers. These methods can deal more accurately with real-world problems, incorporating in their solution a trade-off between the objectives in a single run. The following sections detail these two sets of approaches

6.3.1 Classic Methods

Classical approaches were developed in the field of operational research in order to be applied in multi-criteria decision-making problems. In these approaches, departing from the original problem having a number of objectives, it is built another problem that integrates a single objective. This can be accomplished in different ways as it will be mentioned below, and once this is done the resulting problem can be solved using traditional optimization techniques.

However, regardless of the approach used to build the single objective problem, it is necessary to specify additional information as it will also be mentioned below. A complete overview on this topic is provided in (Coello et al., 2007) and in the next paragraphs we will just briefly describe three approaches in this family of methods:

i **Weighted Aggregation**: It is one of the most popular methods in which a multi-objective problem is converted into a single objective one using a function operator (denominate DM) in order to capture the preferences of the Decision-Maker. The utility function used in this approach is a linear combination of the original objectives and the weights must be set in a way that they reflect the mentioned preferences. To obtain a trade-off between the objectives the problem should be solved a number of times for different values of weights;

ii **Goal Programming**: It is a variation of the weighted aggregation method that aims at minimizing the deviations of the objectives from specified goals. However, as in the weighted aggregation method, information about the goals must be obtained a priori;

iii ε**-Constraint**: It was developed to obtain the Pareto-Front by considering the most important objective as the objective of the single objective problem to be solved and the others are converted in constraints by specifying what is usually known as aspiration values. Typically, the resulting single objective problem is solved several times changing the mentioned aspiration levels that were used to transform all the objectives but one in constraints.

Fig. 6.4 presents the generic structure of the solution algorithm inherent to the classical methods in which "SO" stands for single objective.

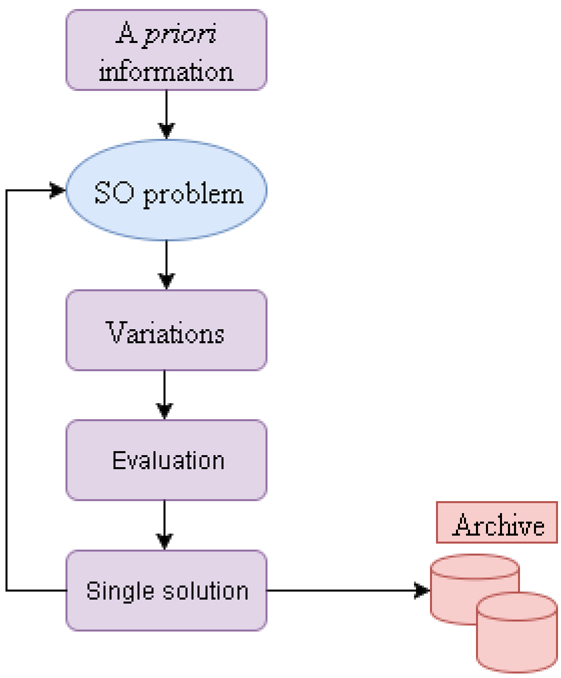

Figure 6.4: Generic structure of the classical methods.

Therefore, classical methods basically incorporate a priori information in order to conduct the decision-making process and find the best compromise solution that results from that information. Besides, the trade-offs between the objectives are obtained by varying aggregation parameters or the mentioned aspiration levels and then solving the problem several times (Lee and El-Sharkawi, 2008). Finally, classical methods have a serious limitation in terms of controlling the diversity of the solutions obtained through the repetition of the solution of the single problem.

6.3.2 Intelligent Methods

Intelligent methods are based on metaheuristics which are adapted to deal with multiobjective problems. Several metaheuristics can be classified as population-based since they are able to work with populations of solutions in the same iteration, which means that this feature can be intelligently used to produce the trade-off between the objectives at each iteration. Thus, non-dominated solutions can be stored iteratively in order to produce an approximation of the Pareto-Front at the end of the process.

Fig. 6.5 presents the generic structure of a solution algorithm using a population-based metaheuristic to solve multiobjective problems. The term variation is general and shall be adapted to the metaheuristic that is used, and it can correspond to reproduction, mutation, replication, etc. After evaluating the solutions over the different objectives, the non-dominated solutions are identified and stored and can be used to select new individuals for the new population in the next iteration through an elitism process, for instance.

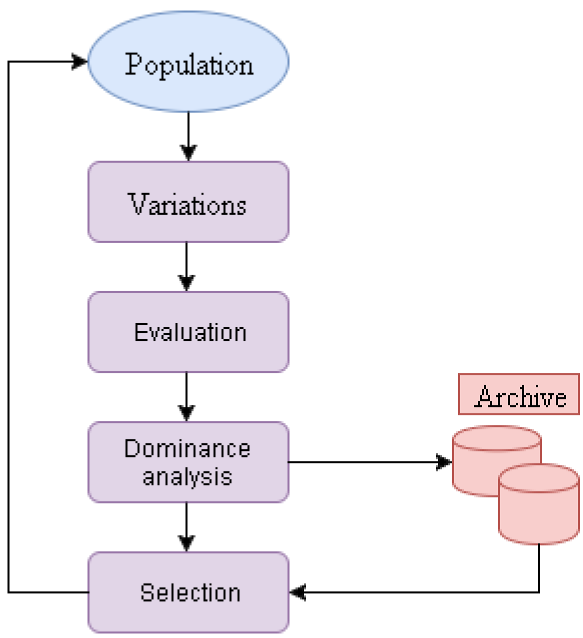

Figure 6.5: Generic structure of the population-based intelligent methods.

Some examples of population-based metaheuristics used to solve multiobjective problems are:

i Haleja & Lin's genetic algorithm (HLGA), (Hajela and Lin, 1992);

ii Vector-Evaluated Genetic Algorithm (VEGA), (Schaffer, 1985);

iii Multiobjective Genetic Algorithm (MOGA), (Fonseca et al., 1993);

iv Strength Pareto Evolutionary Algorithm (SPEA), (Zitzler and Thiele, 1998);

v Nondominated Sorting Genetic Algorithm (NSGA), (Srinivas and Deb, 1994);

vi Nondominated Sorting Genetic Algorithm II (NSGA-II), (Deb et al., 2002);

vii Niched Pareto Genetic Algorithm (NPGA), (Horn et al., 1994);

viii Pareto Archive Evolution Strategy (PAES), (Knowles and Corne, 1999);

ix Multiobjective Particle Swarm Optimization (MOPSO), (Coello et al., 2004);

x Multiobjective Evolutionary Particle Swarm Optimization (MEPSO), (Maciel et al., 2012);

The intelligent methods are able to overcome the limitations of the classical approaches mentioned in the previous subsection. They are able to evaluate several solutions in just one run and do not need a priori information about the problem and objectives, for instance the weights required by aggregation approaches or the aspiration levels necessary by the ε-Constraint method. In the next section we will detail the NSGA-II and the MEPSO algorithms. In one hand NSGA-II is widely used in power system problems as in (Hu et al., 2016) and (Bilil et al., 2014), on the other hand MEPSO is a recent algorithm that provided better results than the first one in some applications of multiobjective problems as in (Maciel et al., 2012).

6.4 Multiobjective evolutionary algorithms

6.4.1 Non-dominated sorting genetic algorithm (NSGA-II)

NSGA-II was proposed in (Deb et al., 2002) in order to overcome the main criticisms directed to the NSGA namely the high computational effort, the lack of elitism and the need for specifying the sharing parameters.

NSGA-II begins with the initialization of the population as usual in metaheuristics. After that, the population is sorted in a number of fronts based on the non-domination concept. As illustrated in Fig. 6.6 the first front is completely non-dominated, the second front is dominated by the first front and so on.

Therefore, each solution is ranked depending on the dominance of the front in which it is included. Additionally, the crowding distance is also calculated for each individual. The crowding distance is an estimation of the perimeter of the cuboid admitting that neighbor solutions are placed at the vertices, as shown in Fig. 6.7.

In this example, the solution *ith* has a crowding distance that is equal to the average of the lengths of the cuboid determined by the solutions $i-1$ and $i+1$. This measure can provide information regarding the density of solutions in a front, or in other words, it provides the distance of each solution to its neighbors, so that a diverse population has larger crowding distances while a population of solutions very concentrated in the same zone of the solution space would have a reduced crowding distance.

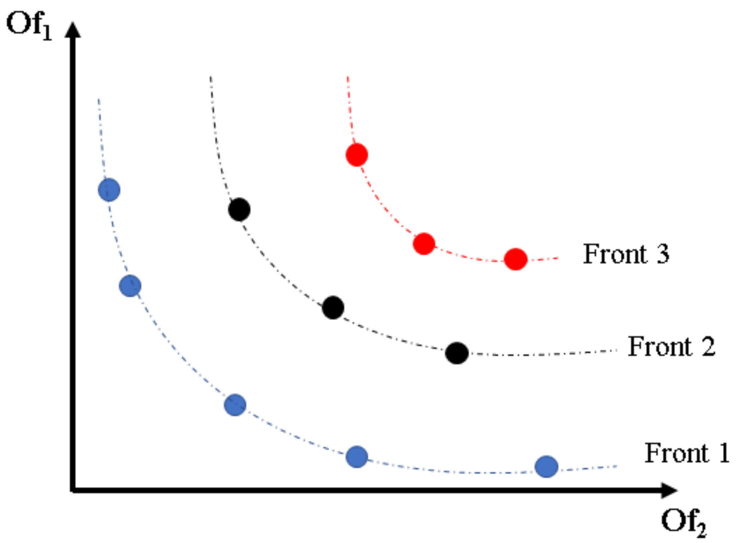

Figure 6.6: Fronts in the NSGA-II procedure.

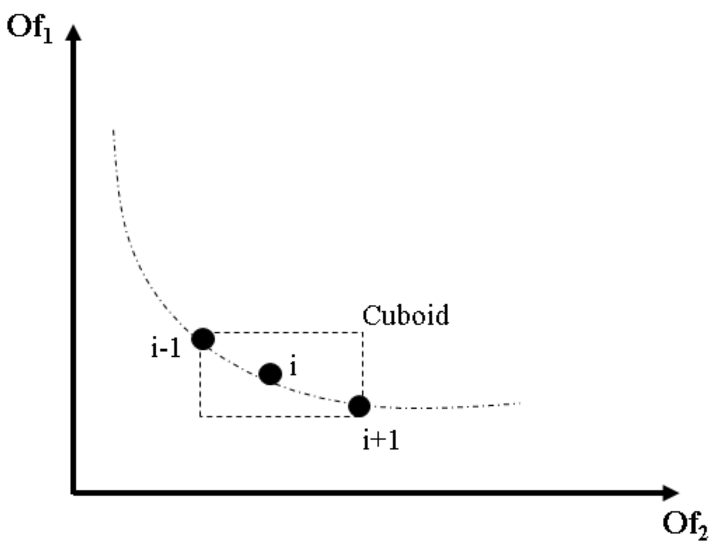

Figure 6.7: Crowding distance.

Thus, the selection is performed by using a tournament procedure based on the rank of dominance and on the crowding distance. The selected individuals are now able to generate new offsprings using the crossover and the mutation operators mentioned in Section 3.5.1. A new iteration begins ranking and sorting the elements of the population and the offsprings, and the stopping criterion uses a pre-defined maximum number of generations. The main blocks of NSGA-II toll and are displayed in Fig. 6.8.

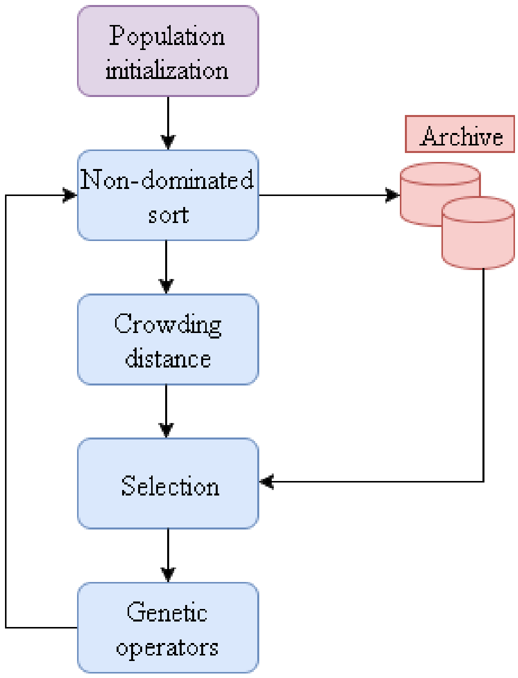

Figure 6.8: Main blocks of NSGA-II algorithm.

6.4.2 Multiobjective evolutionary particle swarm optimization (MEPSO)

MEPSO can be interpreted as an hybridization between the EPSO presented in Subsection 3.5.3 and the NSGA-II presented in the previous subsection. This tool was proposed in (Maciel et al., 2012) and uses the concept of dominance to build the Pareto-Front. The mains steps are illustrated in Fig. 6.9 and are described below:

i Initialize the population;

ii Rank and sort all the solutions according to the dominance concept as illustrated in Fig. 6.6. The result of this step is a set of fronts so that each one is dominated by the previous as in Fig 6.6;

iii Archive the non-dominated solutions in the Pareto list (PL) that corresponds to the front 1 in Fig. 6.6;

iv In each of the mentioned fronts select the $gbest$ and the $pbest$. The $gbest$ is chosen in a random way among the solution in the previous front. Taking again the example in Fig 6.6, the $gbest$ in front 2 is selected from the solutions in front 1. Regarding front 1, the $gbest$ is selected in a random way among its solutions. The $pbest$ is associated to each particle and it translates it history. It corresponds to the solution obtained for this particle along the iterative procedure that is located in the lower dominated front;

v Replicate the solutions r times;

vi Perform the mutation according to Eq. (3.37) and Eq. (3.38);

vii Perform the recombination using Eq. (3.39) and Eq. (3.40);

viii Perform the selection block using a tournament selection and return to step i. When the maximum number of generations (iterations) is achieved plot the Pareto-Front PL.

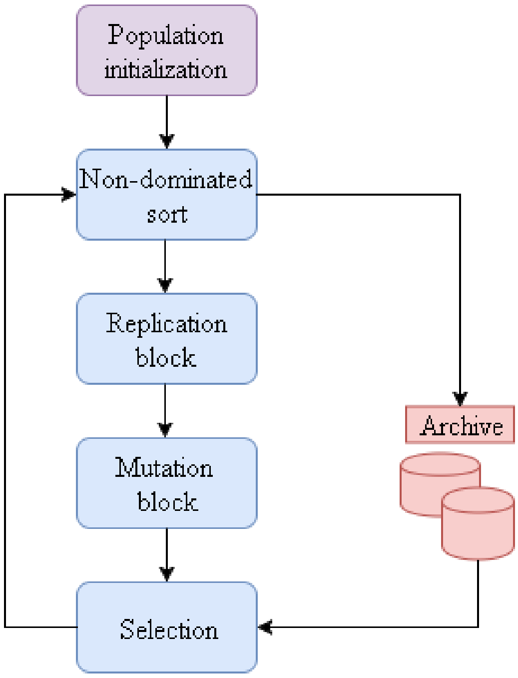

Figure 6.9: Main blocks of MEPSO tool.

6.5 Performance evaluation

There are several Multiobjective Evolutionary Algorithms, MOEAs, described in the literature, which means that their comparison and performance evaluation is a relevant issue. This evaluation is usually based on the comparison of the Pareto-Front built by the approach under analysis with the real Pareto-Front of the problem, admitting that this true front is available from a reference method.

In a similar way to the approach adopted in (Maciel et al., 2012), this comparison requires determining a suitable Pareto-Front beforehand. Although the true Pareto-Front is usually not available, the solutions obtained from running several multiobjective tools can be combined to estimate the true front. In this sense, (Coello et al., 2007) details a number of metrics to assist this performance evaluation, although it is clear that no single metric is able to fully evaluate all the capabilities of a MOEA and therefore they should be carefully used especially when interpreting the results.

Finally, the performance evaluation used in this work has the main objective of assessing the quality of the Pareto-Front built by the algorithm developed in the scope of this research and that will be detailed in Section 6.6 by comparing it with the results provided by the NSGA-II and the MEPSO regarding the accuracy, the spread and the distribution of the solutions along the front. The next paragraphs detail the four metrics that were used for this purpose.

6.5.1 Error Ratio

This metric returns the percentage of solutions in the calculated Pareto-Front (PF_{know}) which do not belong to the true Pareto-Front (PF_{true}) and it is given by Eq. (6.6). This metric can be used to evaluate the accuracy of the PF_{know} in discrete search spaces. In Eq. (6.6) npf is the number of solutions in PF_{know} and e_i is zero if a solution i that is included in PF_{know} belongs to PF_{true} and it is one otherwise. It is clear that the calculated Pareto-Front has an increased quality as the value of ER is more reduced. A result of 0 for this metric indicates that the PF_{know} and the PF_{true} fronts coincide.

$$ER = \sum_{i=1}^{npf} \frac{e_i}{npf} \tag{6.6}$$

6.5.2 General Distance

This metric indicates how far PF_{know} is from PF_{true}. It is given by Eq. (6.7) in which ed represents the Euclidean distance between each solution in PF_{know} to the nearest solution in PF_{true}. In this case, the front PF_{know} is of better quality as the GD gets smaller.

$$GD = \frac{\sqrt{\sum_{i=1}^{npf} ed_i^2}}{npf} \tag{6.7}$$

6.5.3 Pareto-Front Ratio

This metric corresponds to the percentage of points in the calculated Pareto Front that are in the true front and it is given by Eq. (6.8). The quality of the calculated front is higher as the value of PFR gets larger.

$$PFR = \frac{|PF_{know} \cap PF_{true}|}{PF_{true}} \tag{6.8}$$

6.5.4 Relative Spacing

This metric is used to measure the spread and the distribution of the solutions throughout PF_{know} and it assesses how well PF_{know} is distributed. Admitting again a multi objective problem with two objectives, OF_1 and OF_2, this metric is given by Eq. (6.9) and Eq. (6.10) in which D_i is the relative distance between consecutive solutions (i=1,...,npf) and D_m is the mean of all D_i.

$$D_i = \frac{OF_1^i - OF_1^j}{OF_1^i} + \frac{OF_2^i - OF_2^j}{OF_2^i}, \forall i, j \in PF_{know} \wedge j = i + 1 \tag{6.9}$$

$$RS = \sqrt{\frac{1}{npf - 1} . \sum_{i=1}^{npf} (D_m - D_i))} \tag{6.10}$$

6.6 Proposed Multiobjective Evolutionary Algorithm

Several researchers have been proposing multiobjective versions of the EPSO and PSO as in (Maciel et al., 2012), (Lin et al., 2015), (Meza et al., 2017) to address a wide number of power system problems.

Accordingly, we adopted the term MEPSO-II (similar to what happened when NSGA was enhanced to NSGA-II) to stand for Multi-Population and Multiobjective Evolutionary Particle Swarm Optimization. Although the name similarity, the proposed method is an original MO extension of the EPSO algorithm and it combines characteristics and important concepts of evolutionary computation and multi agent population methods.

In Section 6.7, the developed MEPSO-II is compared against the original MEPSO and with the NSGA-II considering the minimization of the investment costs and of the Expected Power Not Supplied (EPNS) as conflicting objectives. In this comparison, MEPSO is important because it corresponds to the first multiobjective version of EPSO and NSGA-II is used for comparison purposes in the vast majority of studies dealing with the multiobjective TEP formulations as in (Hajebrahimi et al., 2017), (Doagou-Mojarrad et al., 2016) and (Arabali et al., 2014).

6.6.1 Motivation

The MEPSO-II tool was developed in scope of this research to address multiobjective problems. According to its name, MEPSO-II works with a number of populations, and this number is equal to the number of objectives in the problem. After initializing each population, each one evolves in parallel to the others in order to optimize the objective to which it is associated. At the end of each iteration all populations are compared in order to extract the non-dominated solutions and to continue the search. In this way the concepts of $gbest$ and $pbest$ used in MEPSO-II refer to the best individual of each population and to the best solution identified to each particle, in a similar way to was mentioned for EPSO in Section 3.5.3.

The main motivations for the development of the MEPSO-II tool are detailed below:

i The NSGA-II (Deb et al., 2002) and the MEPSO (Maciel et al., 2012) use a pre-defined maximum number of iterations as stopping criterion. This does not ensure the convergence of the problem since the random parameters typical of evolutionary computation can originate the algorithms to converge to different solutions, sometimes taking much more iterations than in others. In this case, the MEPSO-II converges if a predefined number of iterations are run without observing changes in the best individual of each population. This way, we ensure that the evolutionary process converges having in mind that in multiobjective problems the concepts of global and local optima are replaced by the concept of non-dominance already mentioned in Section 6.2.2. The relevant issue is that if a pre-defined maximum number of iterations is used, the populations can still present a considerable diversity when the process ends and the Pareto-Front could still be improved if an additional number of iterations was done. This means that simply running a maximum number of iterations may not ensure that a stable Pareto-Front is obtained. Differently, stopping only if the best individual in each population is unchanged for a specified number of iterations is a far more reliable criterion to obtain a good quality and stable final front;

ii In MEPSO and NSGA-II the population is divided in different fronts and their evolution is obtained considering individuals selected from internal fronts taking into account the non-dominated sorting and crowding distance rank concepts. This process may ensure the *dominating effect* illustrated in Fig. 6.10 in terms of identifying new solutions that dominate already existing ones. However, it will hardly ensure the *scattering effect* in terms of being able to enlarge the area covered by the Pareto-Front and this is important to build better quality fronts. Differently, MEPSO-II works with as many populations as the number of objectives and each one evolves towards the $gbest$ (always related with the best fitness function of the corresponding population) and $pbest$ (always related with the best fitness function of each individual). As $pbest$ is always in an internal front it ensures the *dominating effect* while the *scattering effect* is ensured by the $gbest$ that is always located in the extreme points of the Pareto-Front;

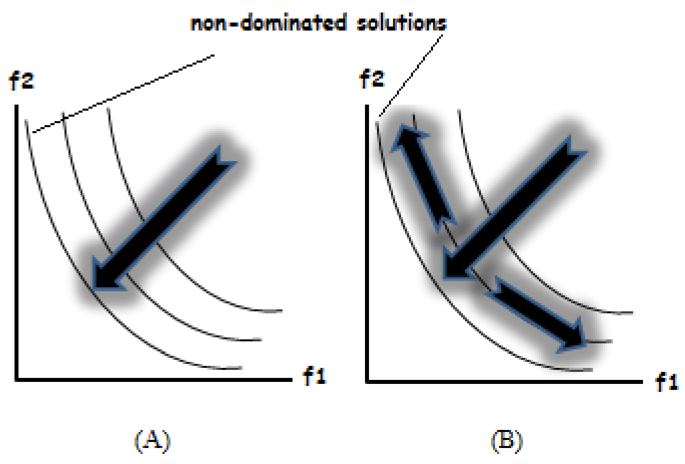

Figure 6.10: The dominating (A) and scattering (B) effects.

iii The MEPSO and the NSGA-II tools build the population for the next generation based on the less dominated individuals of the current population. However, a dominated solution may evolve to a non-dominated one in future generations if its code undergoes some change for instance when performing the mutation or replication steps. The MEPSO and the NSGA-II do not allow this type of change and this may also compromise the diversity of the population. Differently, the MEPSO-II builds the populations for the next generation using an elite that includes the non-dominated solutions. The population is then completed using a tournament selection.

6.6.2 Pareto-Front exploitation via MEPSO-II

MEPSO-II aims at exploiting in a more accurate way the non-dominated solutions in the search space. Fig. 6.10 illustrates the main advantage of the proposed tool over the MEPSO and the NSGA-II tools. Fig. 6.10 (A) illustrates the improvement of the front due to the *dominating effect*, and the *scattering effect* in terms of widening the Pareto-Front is illustrated in Fig.6.10 (B).

The *dominating effect* is responsible for forcing the Pareto-Front as much as possible towards the non-dominance zone, while the *scattering effect* is responsible for pushing the solutions towards the extremes points of the Pareto-Front in order to enlarge its covered area. The elite set ensures the *dominating effect* while the movement rule of the particles inherent to the EPSO algorithm and the corresponding update of the best individual in each population according to the respective objective function ensures the *scattering effect*.

Finally, the diversity of each population is ensured by the combination, at the end of each iteration, of the population's individuals through the elitism process. This procedure guarantees that the non-dominated solutions considering all parallel populations are passed to the next generation. In order to complete the populations, it is used a typical tournament selection comparing pairs of solutions. This comparison also contributes to improve that diversity.

6.6.3 MEPSO-II Formulation

The initial populations, one per objective, are created randomly and each of them is evaluated according to the objective to which it is associated. After that, each population is cloned r times, as in the EPSO algorithm presented in Section 3.5.3. The weights and the best individual found until the current iteration for each population are mutated using Eq. (6.11) and Eq. (6.12) that were presented in Section 3.5.3 and are re-written here.

$$w_{ij}^{*it+1} = 0,5.rand - \frac{1}{1+e^{-w_{ij}^{*it}}} \tag{6.11}$$

$$g_{best}^{*} = gbest + round(2.w_{i4}^{*it+1} - 1) \tag{6.12}$$

The sigmoid function in Eq. (6.11) is used because of its chaotic behavior and as a way to keep the self-adaptation capabilities of the swarms while at the same time controlling their amplitude variations. The use of this sigmoid function is also reported to introduce changes in the position of the particles so that in case they are trapped in a local optimum it will then be possible to more easily escape from it (Da Rocha and Saraiva, 2012).

Once the mutation step is complete, new offsprings are created for each particle in each cloned population using the EPSO movement rule and rounding up the value obtained for each position to integers.

The position of a particle i in iteration $it + 1$ is given by Eq. (6.14) as a result of the addition of its position in iteration it with the velocity vector v that is given by Eq. (6.13) from Section 3.5.3 that are re-written here. The communication factor Ψ in Eq. (6.13) is used to control the information transmitted by the particles about the collective knowledge inside the swarm (Miranda et al., 2008).

$$\nu_i^{it+1} = w_{i1}^{*it+1}.\nu_i^{it} + w_{i2}^{*it+1}.(p_{best} - \chi_i^{it}) + w_{i3}^{*it+1}.rand_2.(g_{best}^{*} - \chi_i^{it}).\Psi \qquad (6.13)$$

$$\chi_i^{it+1} = \chi_i^{it} + \nu_i^{it+1} \qquad (6.14)$$

In order to characterize each solution in each population, it is obtained the associated investment cost (OF_1) and the EPNS (OF_2). Thus, given a solution, that is an individual in one population, its feasibility is analysed running an AC-OPF for the expected annual peak demand. If this solution is feasible, i.e., it meets the peak demand without presenting any violations of the system constraints and so yielding a zero value for PNS, the EPNS is calculated. Otherwise, in order to save computation time, the EPNS is not estimated and the evaluation function of this solution is just penalized to ensure that it is eliminated along the evolution process.

The objective function related to the investment cost (OF_1) is obtained using Eq. (6.15) to Eq. (6.18) presented in Section 5.8, and that are presented again to facilitate reading this chapter.

$$OF_1 = C_{inv,p} = \sum_{eq=1}^{neq} \sum_{p=1}^{np} C_{eq,p} \qquad (6.15)$$

$$C_{eq,p} = Cap_{eq}.(\delta_{eq,p} - \delta_{eq,p-1}) \qquad (6.16)$$

$$\delta_{eq,p} = 0, \forall eq \in \Omega^{ce} \ \wedge \forall p < T_{eq}^{com} \qquad (6.17)$$

$$\delta_{eq,p-1} \leq \delta_{eq,p}, \forall eq \in \Omega^{ce} \wedge \ \forall p \qquad (6.18)$$

The second objective function, OF_2, corresponds to the addition of the EPNS values estimated for each period of the planning horizon by Eq. (6.19) and Eq. (6.20). In these expression $EPNS_p$ represents the EPNS in period p, nsa is the number of equipment availability scenarios and PNS_{sa} is the associated PNS. For each period p, we use the non-chronological Monte Carlo Simulation (MCS) detailed in Section 5.5.2 in order to generate states reflecting the life cycle of transmission lines, cables, transformers and generating units in terms of operation and failure periods. In each state some equipments are available and in operation while some others are affected by failures and the equipment random outages are obtained by sampling for each equipment a uniformly distributed random number ranging from 0 to 1.

$$OF_2 = \sum_{p=1}^{np} EPNS_p \tag{6.19}$$

$$EPNS_p = \frac{1}{nsa} \sum_{sa=1}^{nsa} PNS_{sa} \tag{6.20}$$

Therefore, an equipment is in the outage state if this sampled number is less than its associated Forced Outage Rate (FOR). In order to reduce the burden associated to the computation of the EPNS, we used the probability metrics based scenario reduction technique described in (Wu et al., 2007) that is reported to reduce the required number of analysed states by a factor of 100.

This technique determines a subset of states to be analysed, with the correspondent probability of each one, ensuring that the states in this subset closely follow the probability distribution of the entire population of possible system states. Besides, in the multi-stage TEP, the number of equipments in the system changes along the years, so that the number of states to be analyzed also varies from year to year.

Finally, all individuals of all populations are ranked and sorted based on the concept of dominance described in Section 6.2.2. The non-dominated solutions are included in the set termed as elite and the elements in this set are always included in the populations to be used in the next generation. After that, the populations are completed through a tournament selection process. In this step, recall that we have r clones for each population each of them having ps particles.

The elitist process works separately for each population. It takes the first particle of each of the r clones, compares the r particles and it survives the one that has the best fitness function in which is the objective function associated to the population.

This procedure is repeated for all ps particles so that at the end a new population is created having the same size of the initial ones and the values of $gbest$ and $pbest$ are updated. This iterative process ends when the $gbest$ in all populations does not change after running a pre-specified number of iterations.

Fig. 6.11 presents the main blocks of the proposed MEPSO-II algorithm assuming for the sake of generality that the problem has n objectives.

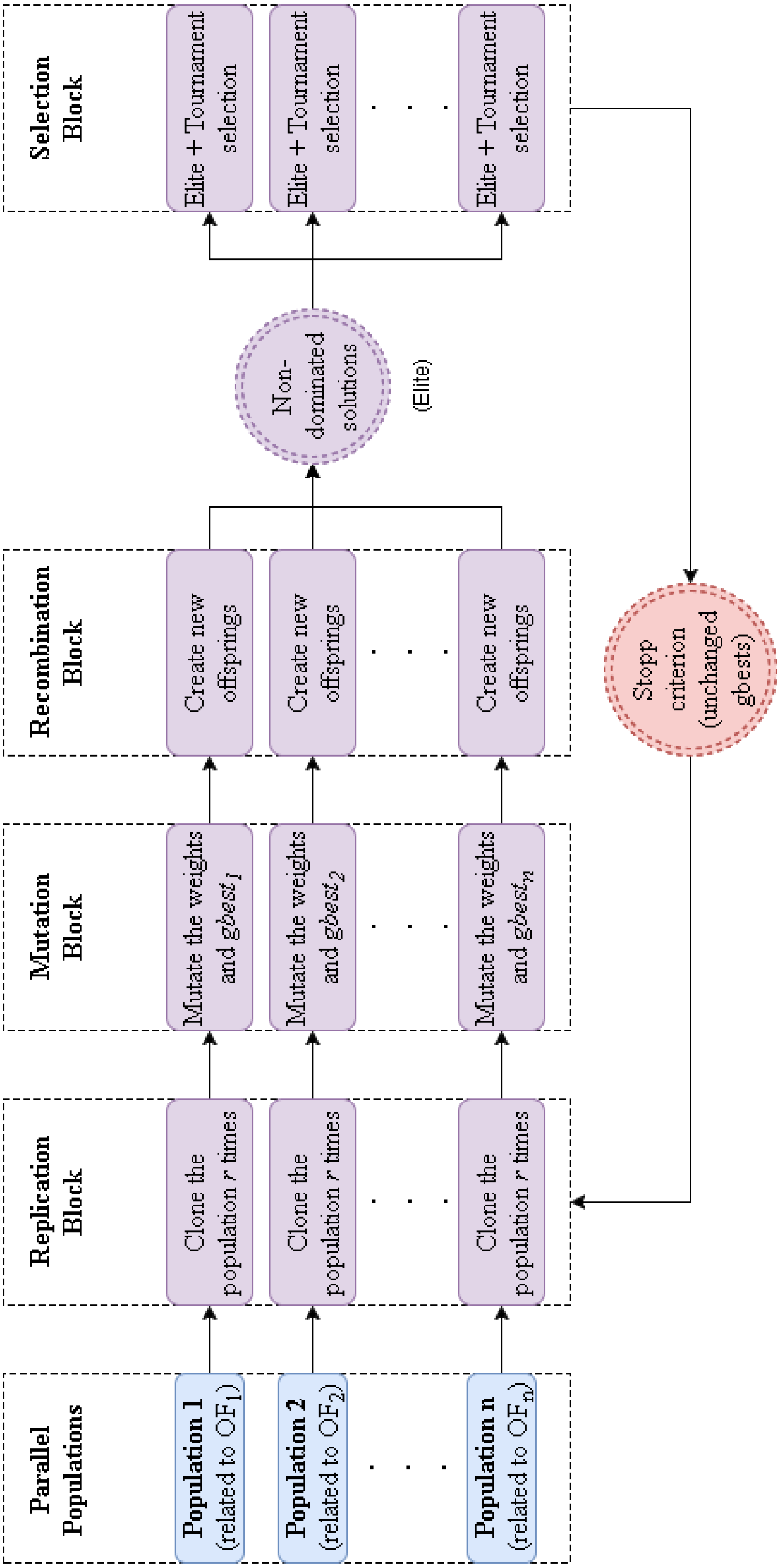

Figure 6.11: The main blocks of MEPSO-II tool.

6.7 Numerical simulations

6.7.1 Outline of the tests

This section presents the results obtained by the proposed MEPSO-II tool and the performance evaluation when compared to the results obtained using MEPSO and NSGA-II. These tools are often used in power system analysis and they are reported to perform very well in obtaining the Pareto-Front of multiobjective problems. The NSGA-II used in this paper is identical to the one presented in (Deb et al., 2002) and the MEPSO corresponds to the approach described in (Maciel et al., 2012).

The parameters used for the NSGA-II and MEPSO are the same as used the ones used in the MEPSO-II. Regarding the stopping criterion, the NSGA-II and the MEPSO use 50 generations for the maximum number of iterations while the MEPSO-II uses a pre specified number of iterations without changing the best solution as the stopping criterion.

As evolutionary computation may output different solutions for multiple runs and may display convergence problems, we ran the MEPSO-II ten times using the IEEE 24 Bus Reliability Test System in order to access the efficiency of the proposed approach. On the other hand, as TEP problems present a non-linear and non-convex nature that can lead to a prohibitive computational effort, the Midwest 118-Bus American Electric Power System was used in order to check the scalability of the proposed method. In this case, the evaluation was done just running the problem once.

As the number of AC-OPFs required to estimate the PNS and EPNS values is large, in these simulations we used the interior point method available in the solver (Zimmerman et al., 2011) to solve the mentioned OPF problems. Besides, to reduce the computational burden required by these calculations, all the simulations were run using parallel computing in MATLAB on an Intel i7, 3.4GHz, 16 GB RAM. Finally, it is important to note that the TEP literature reports results for models using different objectives and different versions of the test systems. This lack of uniformity means that the literature does not provide results to immediately compare existing approaches with MEPSO-II. This difficulty was the main motivation to conduct the comparative analysis that will be reported in the next subsections.

6.7.2 General data

All the tests were done using a 10-years planning horizon. The simulations were performed using a penalization factor for PNS equal to $10^9\$/MW$ and after some trial runs the number of particles in the two populations was set at 40 particles because this was a good compromise between the quality of the results and the calculation time.

We used a discount rate of 5% and a load growth of 2.5% per year in line with typical values used in recent years for power system simulations although this does not represent any constraint for the model and different values can easily be tested. For both test systems, the forced outage rate of generating units is set at 4% and for cables, transformers and transmission lines we used 1%, the commissioning time is considered 1 year for all equipments in both test systems.

Although these values are very often used in the literature, it is clear that if another network is analysed different values will eventually have to be used. The loads of both test systems are modeled as negative real power injections with associated negative costs as described in (Zimmerman et al., 2011). Tables 6.1 and 6.2 include the values of the annual peak demand for the RTS 24 Bus and IEEE 118 Bus Test Systems respectively and Table 6.3 gives the list of the candidate equipments for the two systems.

Table 6.1: Annual peak load forecast - RTS 24 bus

Year	1	2	3	4	5
Peak load (MW)	5700.00	5842.50	5988.56	6138.27	6291.73
Year	6	7	8	9	10
Peak load (MW)	6449.02	6610.25	6775.51	6944.89	7118.52

Table 6.2: Annual peak load forecast - IEEE 118 bus

Year	1	2	3	4	5
Peak load (MW)	6363.00	6522.07	6685.12	6852.25	7023.56
Year	6	7	8	9	10
Peak load (MW)	7199.15	7379.13	7563.60	7752.70	7946.51

Table 6.3: List of candidate equipment

Candidate	RTS 24 Bus Test System				118 Bus Test System			
	Equipment	From	To	Cost (103 US$)	Equipment	From	To	Cost (103 US$)
1	138 kV line	1	3	55.00	138 kV Line	5	6	54.00
2	138 kV line	2	6	50.00	345 kV Line	9	10	161.00
3	138 kV line	2	6	50.00	345 kV Line	8	30	50.40
4	138 kV line	2	6	50.00	345 kV Line	8	30	50.40
5	138 kV line	8	10	43.00	138 kV Line	49	51	137.00
6	138 kV cable	6	10	16.00	138 kV Line	59	61	150.00
7	230 kV line	12	13	66.00	138 kV Line	47	69	277.80
8	230 kV line	14	16	54.00	138 kV Line	69	77	101.00
9	230 kV line	14	16	54.00	138 kV Line	77	78	12.40
10	Transformer	3	24	50.00	138 kV Line	79	80	70.40
11	138 kV line	7	8	16.00	138 kV Line	94	100	58.00
12	138 kV line	7	8	16.00	138 kV Line	110	111	75.50
13	Transformer	9	12	50.00	345 kV Line	30	38	54.00
14	Transformer	9	11	50.00	138 kV Line	94	95	43.40
15	Transformer	10	11	50.00	138 kV Line	17	113	30.10
16	Transformer	10	12	50.00	138 kV Line	23	32	151.30
17	138 kV line	1	5	22.00	345 kV Line	8	9	152.50
18	138 kV line	2	4	33.00	138 kV Line	82	83	36.65
19	230 kV line	20	23	30.00	138 kV Line	37	39	106.00
20	230 kV line	17	18	20.00	Transformer	68	116	20.25

This list includes overhead lines, cables and transformers as these are the most typical components in TEP formulations. However, this list can include other elements as var devices, provided that for each element we specify its possible connection bus and investment cost. Although, using parallel computation reduces the computational burden, the numerical simulations were time consuming because there are 10^{21} combinations of equipments to perform the expansion for each system given the number of elements in the list of candidates and the number of periods in the horizon.

6.7.3 Results of the IEEE RTS 24 bus - 10 runs

The topology and data of the IEEE 24 Bus RTS is available in Appendix A.0.1. However, the values of the original loads were duplicated and the installed capacity of all generators were tripled (real and reactive) in order to turn the network more stressed.

In order to analyse the convergence behavior of the MEPSO-II tool, we solved the TEP problem setting the stop criterion in six different thresholds as 5, 10, 15, 20, 25 and 30 iterations with the same $gbest$ for the two parallel populations. The Error Ratio and the computation time for each threshold used in the MEPSO-II tool are presented in Fig. 6.12. According to these results, if the convergence criterion is set at 5 iterations with the same best individual for each population, the Error Ratio of the Pareto-Front is 30$\%$ with a computation time around 37 minutes.

On the other hand, setting the convergence criterion in 30 iterations, the Error Ratio becomes null, but this requires a time about 5.5 times bigger than the one associated the time required to converge considering the 5 iteration threshold. These results confirm one of the contributions of the proposed tool, that is, it provides a better control of the solution convergence, as mentioned in Section 6.6.

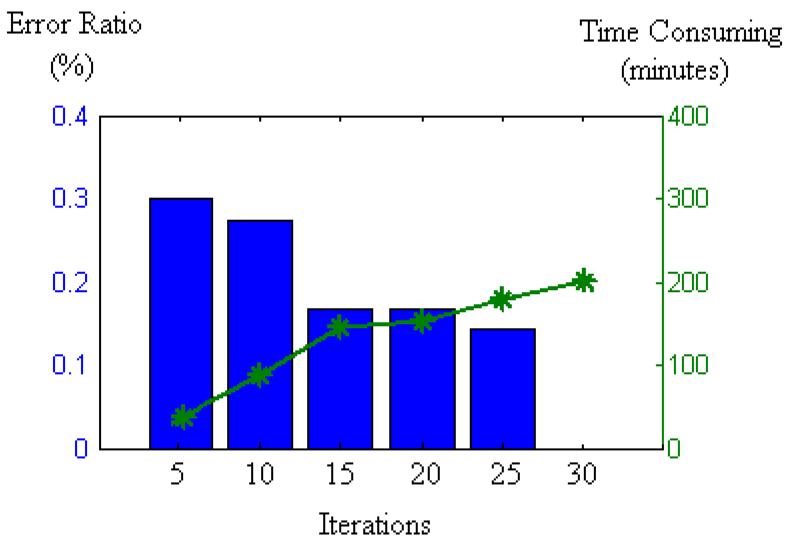

Figure 6.12: Error ratio and computation time for the IEEE 24 Bus Test System.

If a larger number of iterations with the same best individual was required for convergence, the computational time would increase taking into account that for the 24-Bus Test System we ran the problem 10 times.

However, if a larger number of iterations was used, the results would be even more favorable to the MEPSO-II, as the Pareto-Front provided by the MEPSO-II is generally closer to the real one. It should be mentioned that the quality of the front built by each of these three tools is evaluated comparing each of them with the true front. This true front was built taking into account all the solutions obtained by the MEPSO, NSGA-II and MEPSO-II tools and using the concept of dominance between these solutions to extract the non-dominated solutions that will then integrate the true front (

In order to further analyze the convergence and the efficiency of the construction of the Pareto-Front, we ran the TEP problem ten times using the 24-Bus Test System. In this case, the convergence criterion was set in terms of running 10 iterations with the same $gbest$ for the two parallel populations. The Pareto-Fronts built by the proposed MEPSO-II tool as well as by the MEPSO and NSGA-II tools are displayed in Fig. 6.13 to Fig. 6.22 for each of these ten simulations.

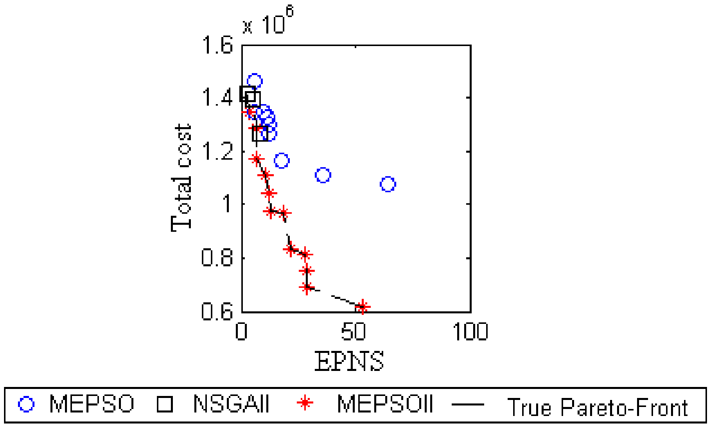

Figure 6.13: Simulation 1 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

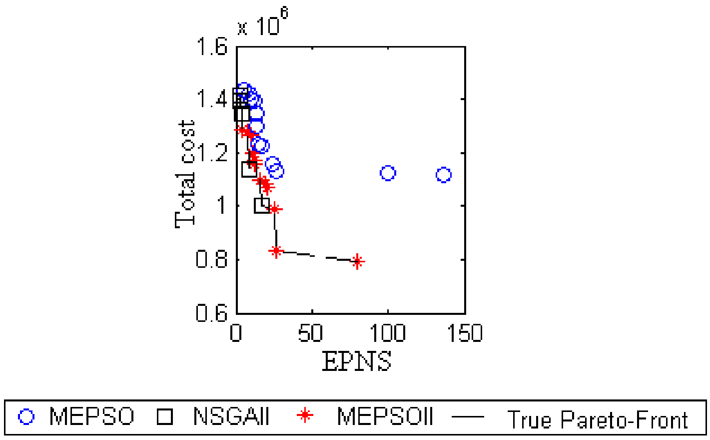

Figure 6.14: Simulation 2 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

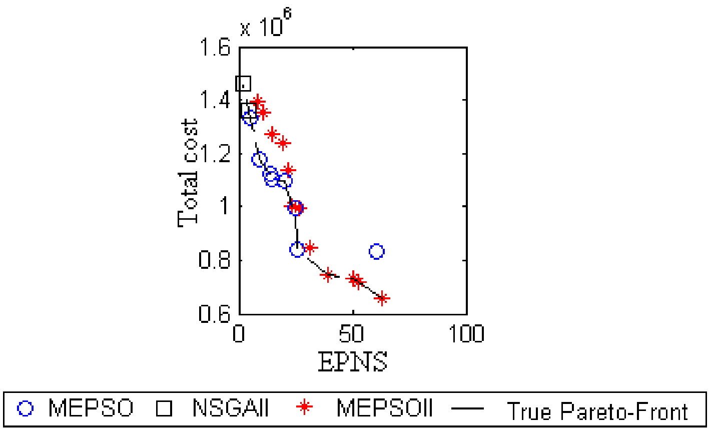

Figure 6.15: Simulation 3 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

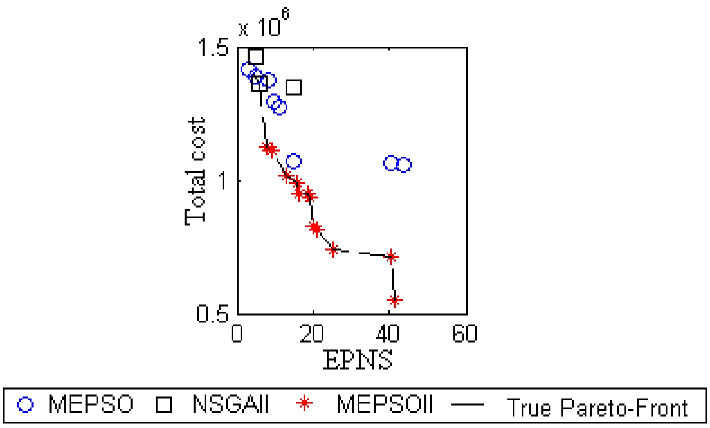

Figure 6.16: Simulation 4 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

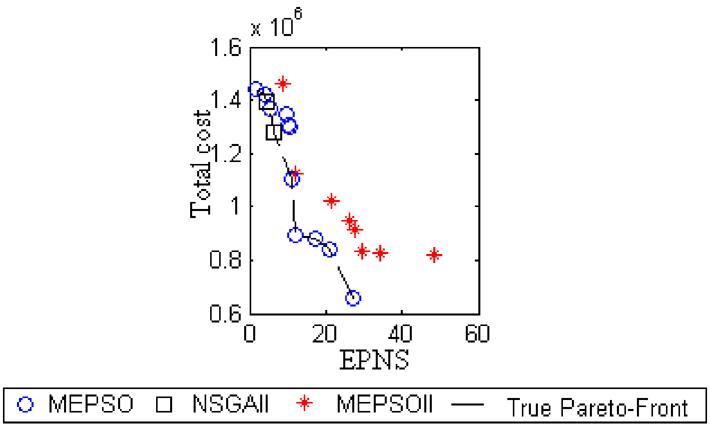

Figure 6.17: Simulation 5 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

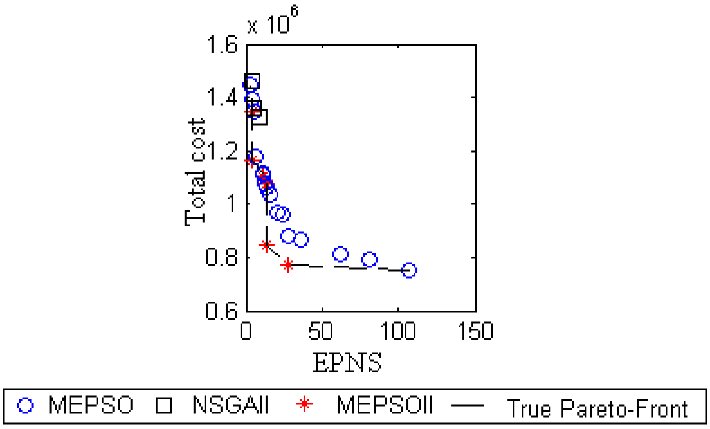

Figure 6.18: Simulation 6 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

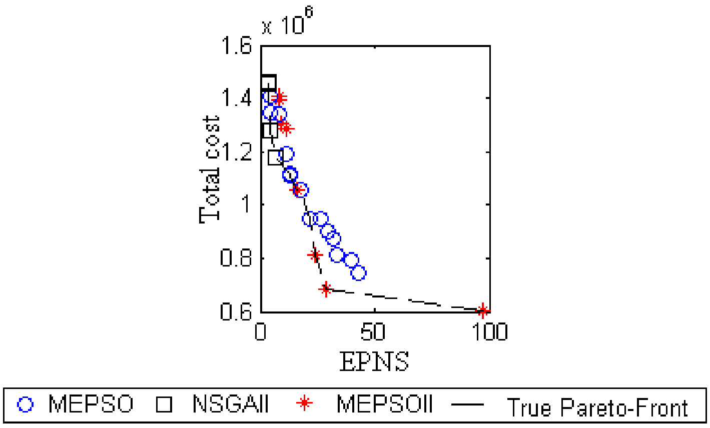

Figure 6.19: Simulation 7 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

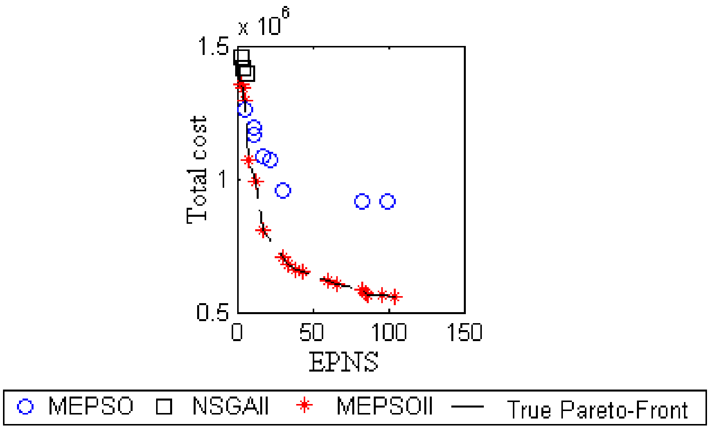

Figure 6.20: Simulation 8 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

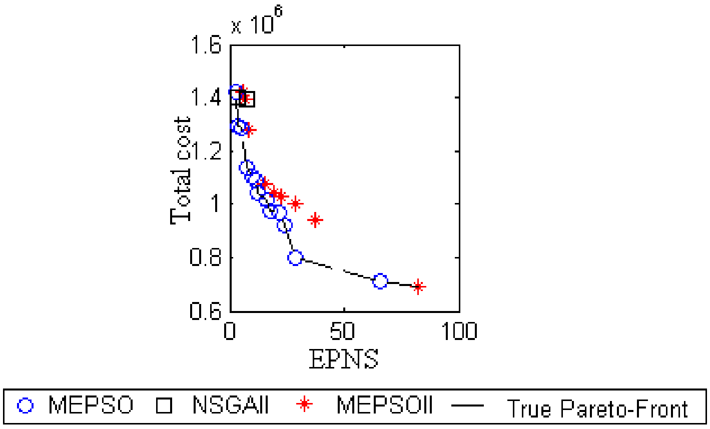

Figure 6.21: Simulation 9 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

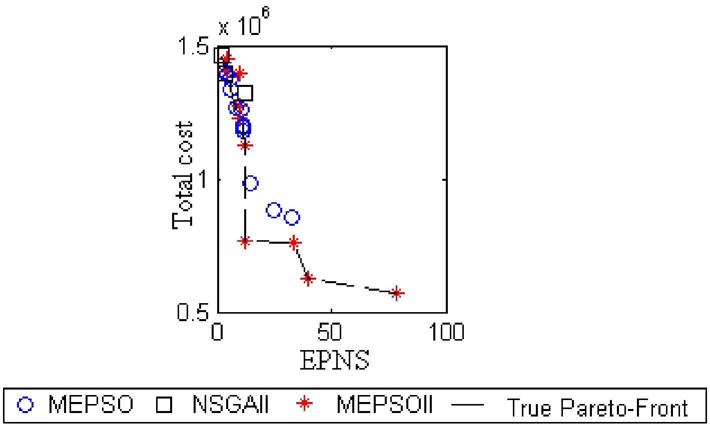

Figure 6.22: Simulation 10 of 10 - MEPSO, NSGA-II and MEPSO-II - RTS 24 Bus.

The performance of the three analysed tools in terms of *Error Ratio*, *General Distance*, *Pareto-Front Ratio* and *Relative Spacing* over the ten simulation runs is provided in Fig. 6.23.

Although in simulations 5 and 9 displayed in Fig. 6.17 and Fig. 6.21 respectively, the MEPSO-II presented worse results than those obtained by the MEPSO and NSGA-II, the proposed model provides a smaller Error Ratio, a smaller General Distance, a larger Pareto-Front Ratio and a better distribution of solutions over the front when compared with the Pareto Fronts built by the two used alternative tools over the ten simulations.

6.7.4 Results for the single run using the IEEE 118 bus system

The data for the IEEE 118-Bus Test System is provided in Appendix A.0.2. Fig. 6.24 presents the Pareto-Front obtained by the proposed toll as well as the Pareto-Fronts built by MEPSO and NSGA-II.

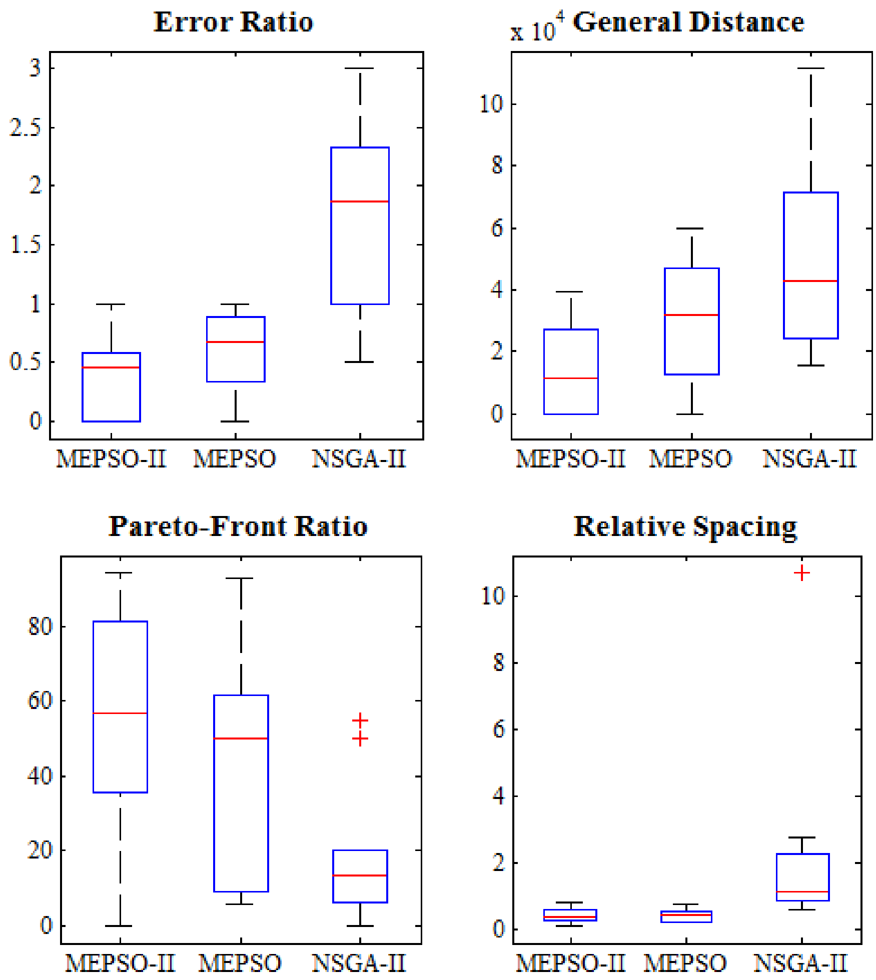

Figure 6.23: Detailed performance for MEPSO-II, MEPSO and NSGA-II using the IEEE 24 Bus Test System for 10 runs.

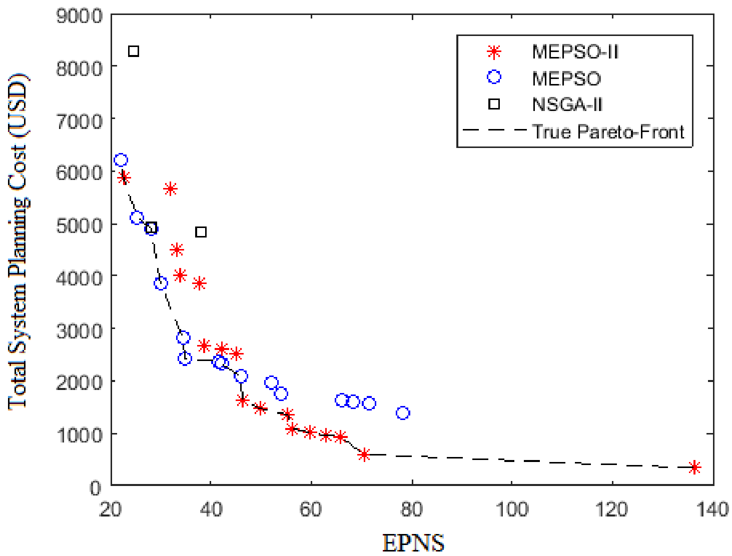

Figure 6.24: Results for the 118 Bus Test System.

Table 6.4 presents the metrics to compare the results obtained using the three analysed tools applied to the 118 Bus Test System.

Table 6.4: Metrics from MEPSO-II, MEPSSO and NSGA-II

	MEPSO-II	MEPSO	NSGA-II
Error ratio	0.4118	0.5333	3.3333
General distance	$0.1332.10^3$	$0.0660.10^3$	$1.1957.10^3$
Pareto-front ratio	50	45	5
Relative spacing	0.3043	0.3232	0.8763

Similarly to the results reported in Subsection 6.7.3, the MEPSO-II presents a better performance regarding these metrics, which means that it has a far larger percentage of points in the true Pareto-Front, a shorter distance to the true Pareto-Front and a smaller error regarding the built Pareto-Front when compared to the results provided by the other two MO tools. In order to build the Pareto- Fronts, the MEPSO-II requires more time than the other two tested tools, but TEP is recognized as an off-line study which means that taking more time to get better quality results can be seen as an affordable trade off.

6.8 Conclusions

The changes experienced by power systems over the last years turned very complex the development of simulation tools to address long term planning problems. However, long term planning is still an important activity namely as a way to ensure on the long term the safe and secure supply of the demand. In line with these concerns, this chapter presented a new tool that is able to deal with the multiobjective nature of the transmission expansion planning problems while providing better quality results when compared with other tools.

The developed approach was applied to the TEP problem considering the minimization of the system total costs that comprises investment costs and the operation costs together with the minimization of the expected power not supplied, which is estimated taking into account the uncertain behavior associated with the lifetime of system components using the respective FORs.

The novel MEPSO-II tool uses parallel populations to exploit in a better way the non-dominated solutions through the dominating and the scattering effects. These effects enabled the development of a robust mechanism to build the Pareto Front as it was illustrated by comparing the results provided by MEPSO-II with the ones provided by two well-disseminated and consolidated tools described in the literature: the MEPSO and the NSGA-II. The results are compared using the statistical metrics Error Ratio, General Distance, Pareto-Front Ratio and Relative Spacing detailed in Fig. 6.23 and Table 6.4 for the two tested systems, and this comparison is very favorable to the MEPSO-II both regarding the IEEE 24 Bus and the IEEE 118 Bus Test Systems.

The developed MEPSO-II tool can be easily adapted to consider demand and generation uncertainties, for instance associated to hydro, wind or solar resources. This would require specifying probabilistic distributions for these variables and sampling values for each of them to be used in the evaluation block of the MEPSO-II algorithm. All these characteristics together with the performance of the MEPSO-II algorithm can be used by transmission providers in a fruit full way to build more robust long-term investment plans.

Chapter 7

Conclusions and future work

7.1 Main conclusions

The present Doctoral Thesis addresses the Transmission Expansion Planning, TEP, problem on the perspective of mathematical models, impact of distributed energy resources, uncertainties and multiobective issues. The literature review presented in Chapter 2, enable identifying the way that the mathematical models and computational complexities are addressed on transmission expansion planning problems. Besides, it also enables understanding how the uncertainties affecting the future conditions of the power systems are incorporated in the problem as well as how the decision-making is conducted regarding the different objectives considered by the stakeholders.

The TEP literature review enabled identifying four main gaps related to:

i Mathematical models and relaxations.

The widespread DC-OPF is often used to conduct the planning problem because it is lighter than the full AC-OPF. However, the optimal solutions obtained using the linearized model may not even be a feasible solution regarding the original problem, using AC equations;

ii Impact of distributed energy resources.

The impact of distributed energy resources in the planning task are scarcely addressed in the TEP literature and need to be modeled and assessed. In fact, the spread of DERs can modify the power flow patterns at the transmission-distribution boundary and thus impact on expansion planning studies;

iii Decision-making and uncertainties.

The vast majority of TEP studies considers the peak load, which is seen as the worst-case scenario, to quantify investment requirements. However, high off-peak load scenarios combined with low renewable generation can originate unforeseen bottlenecks and that seems to have not been addressed by the scientific community;

iv multiobjective considerations.

Although a number of studies have addressing the unbundling of the electricity sector, most studies only consider one objective, contrary to the recent and diverse wishes of different stakeholders.

Therefore, this Doctoral Thesis was directed towards the in-depth research regarding these four gaps identified in the literature review. Thus, the main conclusions about the research conducted towards these gaps are:

- **Mathematical models and relaxations**

  The mathematical models used to represent the transmission expansion planning problem, the computational effort required to solve it and the application of meta-heuristic to conduct the problem were fully addressed in Chapter 3. It was verified that even though the DC model can reduce the computational effort by comparing to approaches using the AC model, it underestimates the investments in new equipments because the solution plans obtained with this model can originate violations of several constraints, namely non zero Power Not Supplied, when they are tested using the full AC equations. Furthermore, it was also verified that constructive heuristic algorithms and parallel computing approaches can be efficient tools to reduce the time required to solve the TEP problem in a reliable way. Finally, with the results obtained in Chapter 3, it is also concluded that the Evolutionary Particle Swarm Optimization presents better behavior in finding optimal and sub-optimal solutions when compared to Genetic Algorithms and Particle Swarm Optimization, which are widely used in the literature.

- **Impact of distributed energy resources**

  The main distributed energy resources mentioned in the literature and their impact on the TEP problems are assessed in Chapter 4. The impact of solar distributed generation and electric vehicles was analysed using the results obtained in numerical simulations described in this Chapter. Regarding the solar DG results, it was verified that the optimal expansion plan can remain unchanged, at least for the simulated level of PV penetration, if the peak load occurs after the solar generation period (that is after 6 pm). This suggests that, in some cases, solar DG is not able in an isolated way to reduce the liquid peak load seen by transmission networks and thus contribute to postpone transmission investments and reduce the corresponding cost. In these cases, solar DG should be associated to storage devices or demand response programs should be implemented in order to reduce the investment effort in transmission networks. The conclusions regarding the electric vehicles penetrations are twofold. In one hand, the adoption of a multiple tariff scheme has a strong impact on the demand profile and this will likely originate a large increase of the required investments on the transmission system. On the other hand, the investments in new equipment in the transmission network could be postponed if it is adopted an efficient management approach to control PEVs charging that includes the "valley-filling effect" and/or the "peak-shaving effect".

- **Decision-making and uncertainties**

  Probabilistic models regarding renewable generation and electricity demand in the scope of the TEP problem were addressed in Chapter 5. In this way, a stochastic transmission planning model is conducted using a complete approach using the year-by-year representation of the investment decisions, the adoption of the full AC Optimal Power Flow model and the well-known N-1 contingency criterion.

It has been proven in this chapter that transmission planning considering only the peak load to quantify investment requirements, a practice widely reported in the literature, is not sufficient to ensure the safe operation of the system in normal conditions for any other off-peak load scenarios. In fact, scenarios with a high off-peak load and a low renewable generation have to be taken into account in order to ensure the safe operation of the system. Furthermore, when the operation or unserved energy costs are not considered in the transmission expansion planning exercise, insufficient investment plans can be obtained.

- **Multiobjective consideration**

  The multiobjective consideration of the TEP problems imposed by different stakeholders is addressed in Chapter 6. The multiobjective question was addressed in this chapter through the objectives of investment costs of new equipment for the transmission grid and reliability. These objectives are conflicting, since a higher index of reliability may be related to a greater number of equipment in the network. In this way, the results obtained in this chapter allow to conclude that the multi-objective approach, although is much more complex than the single objective one, gives the decision maker a higher flexibility to operate as well as more information about the solutions presented, which in turn are trade-offs between the optimized objectives.

7.2 Contributions

To facilitate the understanding of the contributions of this Doctoral Thesis, they are presented organized by chapter.

Chapter 3 discusses the mathematical formulation of the TEP problem, the computational effort required to solve it and the algorithms used in its solution. Accordingly, the main contribution of this chapter is the proposed new constructive heuristic algorithm capable of reducing the search space of the problem and, consequently, the time required to solve it. The Security CHA was able to reduce the computational effort in 47% using the AC-OPF model. Furthermore, when the proposed Security CHA is used together with parallel computing, the time required to solve the TEP problem can be reduced by 82%, that is, more than the reduction obtained using the DC model (72%), but in a more reliable way.

Chapter 4 summarized the penetration of distributed energy resources and their impact on the demand seen by transmission system. The main contribution of this chapter is to find out the impacts of distributed solar generation and electric vehicles in the investments on new equipment for the transmission network. Although this type of analysis is very scarce in the literature, it has been proven that these distributed resources influence the demand seen by the transmission network and can change the TEP results depending on the policies adopted to support the investments on DER and the level of their penetration.

Chapter 5 describes the theory and parameters often used to include probabilistic considerations in TEP problems. The simulations conducted in this chapter aimed at answering questions related to the costs associated with the adoption of a degree of robustness in the planning and questions related to how the decision-making process adopted in the planning exercise substantially influences the total cost of the system. Therefore, the contributions obtained are twofold, first of all, a new worst-case parameter was proposed in order to ensure that the system has enough flexibility to overcome scenarios with high off-peak demand and low renewable power. The second contribution is the broad and detailed analysis of the most common decision-making processes adopted in the TEP literature and their impact on the total system cost.

The conflicting objectives associated with different stakeholders in the new, unbundled and restructured electrical sector and the peculiarities of the TEP problem were presented in Chapter 6. Therefore, this chapter describes a new tool, called MEPSO-II, based on computational intelligence techniques to solve a multiobjective TEP formulation. The novel MEPSO-II tool uses parallel populations to exploit in a better way the non-dominated solutions through the dominating and the scattering effects. These effects enabled the development of a robust mechanism to build the Pareto Front as it was illustrated by comparing the results provided by MEPSO-II with the ones provided by two well-disseminated and consolidated tools described in the literature: the MEPSO and the NSGA-II. The results are compared using the statistical metrics Error Ratio, General Distance, Pareto-Front Ratio and Relative Spacing for the two tested systems, and this comparison is very favorable to the MEPSO-II algorithm.

7.3 Answering the research questions

In this section the research questions raised in Chapter 1 are answered. Although, there is not an unique answer for these questions, we give these answers based on the developed work together with some general considerations are also derived in order to help the scientific community to handle the mathematical models, distributed energy resources penetration, uncertainties and multiobjective considerations in TEP problems in a more effective and efficient manner.

Research Question 1:

How to approach the TEP problem in the most realistic way in which the required computational effort does not become prohibitive?

In the last years it was the use of the linearized DC model in most TEP formulations. In this way the TEP problem is solved much more lightly than when using the complete AC model. However, it has been proven with the results provided in Chapter 3 that this linearized model may display unreliable solutions for the transmission planning, that is, the results obtained with the DC model may violate basic constraints of TEP problem, such as presenting power not supplied, when tested using the complete AC model.

In this way we conduct the TEP problem in a more realistic way, using the AC model to capture insights on the system's operating condition and the year-by-year consideration of the investment decisions to ensure the planning holistic view. This approach is computationally much heavier to be solved, and, for this reason, we proposed a new constructive heuristic algorithm to reduce the TEP search space and the time required to solve the problem. This is an efficient and reliable way to conduct the TEP problem. In fact, when the proposed constructive heuristic algorithm is used together with the parallel computing approach, the time required to solve the TEP problem is less than the required by using the DC model.

Research Question 2:

How the distributed energy resources should be considered on the long-term planning with the aim of taking advantages and benefits for the whole electrical system?

The impact of solar distributed generation and electric vehicles on the TEP problem was discussed in Chapter 4. Regarding the impact of the solar distributed generation, the results suggest that the peak load should be between 6 am and 6 pm (the period with solar generation) preferably around 12 a.m. so that the impact is larger, at least for the level of PV penetration that was used in the simulations. If that was the case, in addition to reducing emissions, operating costs and transmission losses, the investment to meet the peak load would also decrease due to the peak load decrease seen by the transmission network. However, transferring the peak load to this interval can be an arduous and costly task, or even impossible. In this way, another plausible solution would be to associate distributed generation with storage devices and DR programs.

Regarding the electric vehicles, their impact on electric demand is directly related to the charging policies, infrastructure and level of penetration. The results of the simulations described in Chapter 4 indicate that multi-tariff schemes may provide worse results than flat tariffs. This is because the electric vehicle owners tend to charge their vehicles at the beginning of the low-tariff period, causing a peak load at that time. In this way, the system needs more equipments (that is, more investments) such as transmission lines, transformers and cables to meet that demand. On the other hand, when the charging policy implies charging the electric vehicles in off-peak periods in which the peak load does not increase (or does not increase so much) the investment in new equipment can be postponed. Finally, an even better scenario corresponds to a charging policy that associates the charging of electric vehicles in off-peak periods and the supply of electricity from the electric vehicles to the main network (V2G services) in peak periods.

Research Question 3:

How the seasonality of water resources and the intermittent nature combined to their low predictability and controllability of wind and solar sources should be addressed and what are their impacts on the long-term planning?

This is the most challenging question addressed in this Doctoral Thesis. Power systems around the world have been changing towards the reduction of GHG emissions and mitigating effects to global warming by using renewable sources. This is a relatively new concern that has gained more relevance with the Kyoto Protocol and more recently with the Paris Agreement on Climate Change. However, the way in which power systems must evolve using these renewable technologies must be studied with caution.

The TEP problem has been conducted over the last years considering the annual peak load, which is seen as the worst case, to quantify investment requirements in the network.

However, the peak load may not correspond to the worst case in systems with large shares of renewable sources. In fact, high off-peak load scenarios combined with low renewable generation can originate unforeseen bottlenecks that need to be considered in the planning task.

Chapter 5 provides some simulations about this issue. The results obtained indicates that the net peak and the load peak should be considered together as parameters in the planning task and not only the load peak as it is usual in TEP literature. Therefore, neglecting the net peak information can result in underestimating the investment in new equipments and thus eventually originating non-zero Power Not Supplied.

Research Question 4:

How the different and conflicting objectives associated to different stakeholders impact the TEP problem and how they should be addressed?

As discussed in Chapter 6, the transmission planning task should address several objectives associated with different stakeholders as the minimization of investment costs, operation costs, GHG emissions, transmission losses, risks, while improving the competition among the generation companies, etc. The most complete way to approach these different objectives is to optimize them at the same time, so the concept of optimal solution no longer has the same meaning as in single objective optimization problems. In fact, multiobjective optimization processes provide a set of solutions known as non-dominated solutions. In this way, the decision maker has more flexibility and information about the conditions and risks of the system to choose the final expansion plan. However, multiobjective TEP is an intensive time-consuming task and has a huge search space with just few feasible solutions, so that there are few tools that can do this analysis efficiently.

As a way of answering this question, the multiobjective tool MEPSO-II was proposed in Chapter 6. This tool yielded a superior performance when compared with the results reported regarding multiobjective tools consolidated in the literature in the solution of the TEP problem.

7.4 Future work and research opportunities

The transmission expansion planning problem considering uncertainties and multiobjective consideration is a broad field and, as mentioned in Chapter 2, there are research opportunities and gaps in the literature that still need the attention of the scientific community.

In this Section, we identify further research areas related to the work developed in each chapter. The general opportunities and research directions in transmission expansion planning problems are described at the end.

Chapter 3 compared AC and DC models for efficacy and time consumed. In addition, the chapter also compares different bio-inspired metaheuristics in the solution of the TEP problem. Finally, a constructive heuristic algorithm is proposed with the purpose of reducing the time required for the solution of the TEP problem. There are opportunities on the computational performance of these mathematical models and compared algorithms.

The computer processing capacity is increasing dramatically each year and can be used in a favorable way to solve complex problems such as the one addressed in this Thesis. The use of mathematical models that are closer to reality can lead to more reliable solutions but require longer solution times. Thus, new computational techniques such as parallel computing and the combination of clustering may be the key so that solution time does not become prohibitive. In this sense, the development of metaheuristics that efficiently travel in the search space also play a fundamental role and deserve attention of the scientific community.

Chapter 4 addressed the distributed energy resources and analyzed their impacts on transmission planning. Distributed energy resources are increasingly gaining space in the grid and will certainly impact on the demand seen by the transmission system. Thus, their inclusion in the mathematical models of TEP problems is undeniable. In this sense, further research is needed to ascertain the impacts of demand response programs. Flexible or interruptible loads can change their consumption profile in order to avoid electricity spikes and the need to include new equipment in the networks, reducing the investment costs (and increasing the operational costs due the DR costs). The impact of storage devices, both in the distribution networks and in the transmission networks, also deserve the attention of the scientific community. These devices may be used to postpone not only investments in the transmission network but also investments in the expansion of generating capacity.

Chapter 5 addressed the uncertainties arising from renewable systems and electric demand, as well as the impact of the different decision-making processes known in the literature. A research opportunity lies in the study and comparison of risk-averse strategies using robust optimization and/or stochastic programming. These models provide more reliable solutions that are able to meet the different future conditions of the system such as low renewable production and outages. Therefore, the research opportunity is in this direction, that is, the TEP is not only looking for a low-cost solution anymore, but also one that is robust/flexible enough to mitigate outage or extreme events.

Chapter 6 provides insights about multiobjective optimization problems and how the TEP problem can be handled considering several conflicting objectives eventually associated to different stakeholders. In this sense, there is a research opportunity to construct tools capable of dealing with this multiobjective question. As the TEP problem is associated to the combinatorial explosion of solution expansion plans, its search space is huge but typically with few feasible solutions. In this way, new tools able to explore the search space in a way that the final set of solutions, the Pareto-Front, is diverse and scattered may be of interest to decision-makers.

Besides the research opportunities related to the work developed in each chapter, we identified gaps in the literature review that were not addressed in this Doctoral Thesis, as follows:

i Use special equipments such as High-Voltage Direct-Current, Flexible Alternating Current Transmission Systems and Fixed series compensation in the planning task. The present Doctoral Thesis just considers the AC transmission lines, cables and transformers as new equipments to be inserted on the grid. However, the mentioned special equipments are receiving increasing attention and should be considered in future TEP works;

ii The use of microgrids and their impact on the TEP problem is also a subject rarely explored in the literature and deserves attention. Microgrids can be used in concomitant transmission planning, i.e. a co- optimization problem. Microgrids can improve the reliability of the power system with a lower investment cost and should be considered in future TEP problems.

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Appendix A

Test Systems Data

A.0.1 IEEE RTS 24 Bus

RTS 24 Bus is presented in Fig. A.1 and has 24 bus, 33 generators, 17 loads, 1 shunt, 38 branches and 5 transformers on its base topology. Besides, the system has two voltage levels, 138 and 230 kV. The initial available generation capacity is 3405 MW while the initial system peak load is 2850 MW.

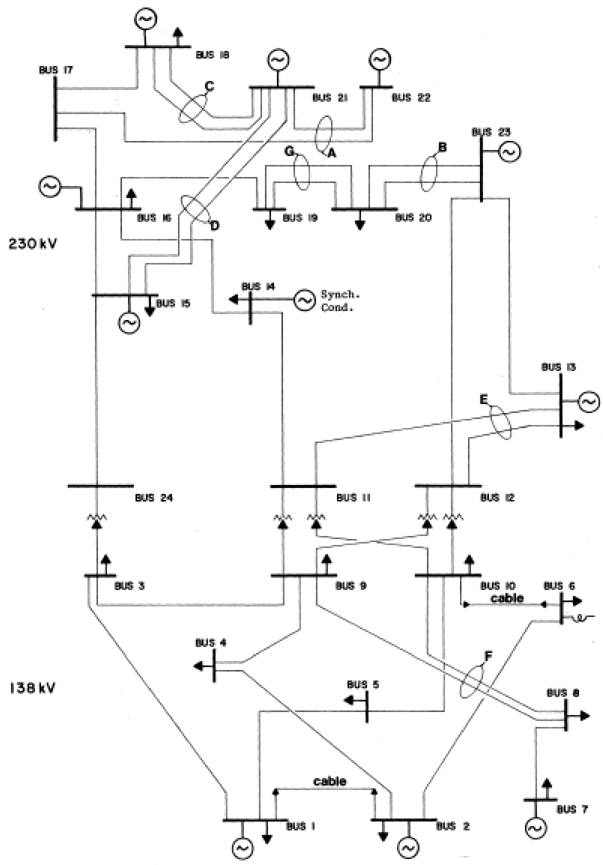

Figure A.1: RTS 24 bus topology.

Bus Data

In Table A.1, the power base is 100 [MVA], bus is the bus number, $type$ is 1 for PQ, 2 for PV, 3 for reference bus and 4 for isolated buses. Pd and Qd are the real power demand and the reactive power demand (peak), Gs and Bs are the shunt conductance and the shunt susceptance (MW demanded and MVAr injected at V = 1.0 p.u), $area$ is the area number, $baseKV$ is the base voltage, $Vmax$ is the maximum voltage magnitude (p.u) and $Vmin$ is the minimum voltage magnitude.

Table A.1: Bus data - RTS 24 Bus Systemn

bus	type	Pd	Qd	Gs	Bs	area	baseKV	Vmax	Vmin
1	2	108	22	0	0	1	138	1.05	0.95
2	2	97	20	0	0	1	138	1.05	0.95
3	1	180	37	0	0	1	138	1.05	0.95
4	1	74	15	0	0	1	138	1.05	0.95
5	1	71	14	0	0	1	138	1.05	0.95
6	1	136	28	0	-100	2	138	1.05	0.95
7	2	125	25	0	0	2	138	1.05	0.95
8	1	171	35	0	0	2	138	1.05	0.95
9	1	175	36	0	0	1	138	1.05	0.95
10	1	195	40	0	0	2	138	1.05	0.95
11	1	0	0	0	0	3	230	1.05	0.95
12	1	0	0	0	0	3	230	1.05	0.95
13	3	265	54	0	0	3	230	1.05	0.95
14	2	194	39	0	0	3	230	1.05	0.95
15	2	317	64	0	0	4	230	1.05	0.95
16	2	100	20	0	0	4	230	1.05	0.95
17	1	0	0	0	0	4	230	1.05	0.95
18	2	333	68	0	0	4	230	1.05	0.95
19	1	181	37	0	0	3	230	1.05	0.95
20	1	128	26	0	0	3	230	1.05	0.95
21	2	0	0	0	0	4	230	1.05	0.95
22	2	0	0	0	0	4	230	1.05	0.95
23	2	0	0	0	0	3	230	1.05	0.95
24	1	0	0	0	0	4	230	1.05	0.95

Generation Data

In Table A.2, bus is the bus number, Pg is the real power output (MW), Qg is the reactive power output (MVAr), $Qmax$ is the maximum reactive power output (MVAr), $Qmin$ is the minimum reactive power output (MVAr), Vg is the voltage magnitude set point (p.u.), $mBase$ is the total MVA base of machine (defaults to power base), $status$ is the machine status (1 for in-service and 0 for out-of-service), $Pmax$ is the maximum real power output (MW) and $Pmin$ is the minimum real power output (MW).

Table A.2: Generation data - RTS 24 Bus System

bus	Pg	Qg	Qmax	Qmin	Vg	mBase	status	Pmax	Pmin
1	10	0	10	0	1.035	100	1	20	16
1	10	0	10	0	1.035	100	1	20	16
1	76	0	30	-25	1.035	100	1	76	15.2
1	76	0	30	-25	1.035	100	1	76	15.2
2	10	0	10	0	1.035	100	1	20	16
2	10	0	10	0	1.035	100	1	20	16
2	76	0	30	-25	1.035	100	1	76	15.2
2	76	0	30	-25	1.035	100	1	76	15.2
7	80	0	60	0	1.025	100	1	100	25
7	80	0	60	0	1.025	100	1	100	25
7	80	0	60	0	1.025	100	1	100	25
13	95.1	0	80	0	1.02	100	1	197	69
13	95.1	0	80	0	1.02	100	1	197	69
13	95.1	0	80	0	1.02	100	1	197	69
14	0	35.3	200	-50	0.98	100	1	0	0
15	12	0	6	0	1.014	100	1	12	2.4
15	12	0	6	0	1.014	100	1	12	2.4
15	12	0	6	0	1.014	100	1	12	2.4
15	12	0	6	0	1.014	100	1	12	2.4
15	12	0	6	0	1.014	100	1	12	2.4
15	155	0	80	-50	1.014	100	1	155	54.3
16	155	0	80	-50	1.017	100	1	155	54.3
18	400	0	200	-50	1.05	100	1	400	100
21	400	0	200	-50	1.05	100	1	400	100
22	50	0	16	-10	1.05	100	1	50	10
22	50	0	16	-10	1.05	100	1	50	10
22	50	0	16	-10	1.05	100	1	50	10
22	50	0	16	-10	1.05	100	1	50	10
22	50	0	16	-10	1.05	100	1	50	10
22	50	0	16	-10	1.05	100	1	50	10
23	155	0	80	-50	1.05	100	1	155	54.3
23	155	0	80	-50	1.05	100	1	155	54.3
23	350	0	150	-25	1.05	100	1	350	140

Branch Data

In Table A.3 $fbus$ is the “from” bus number and $tbus$ is the “to” bus number, r is the resistance (p.u.), x is the reactance (p.u.), b is the total line charging susceptance (p.u.), $rateA$ is the MVA rating A (long term rating), $rateB$ is the MVA rating B (short term rating), $rateC$ is the MVA rating C (emergency rating), $ratio$ is the transformer off nominal turns ratio.

Table A.3: Branch data - RTS 24 Bus System

fbus	tbus	r	x	b	rateA	rateB	rateC	ratio
1	2	0.0026	0.0139	0.4611	175	250	200	0
1	3	0.0546	0.2112	0.0572	175	208	220	0
1	5	0.0218	0.0845	0.0229	175	208	220	0
2	4	0.0328	0.1267	0.0343	175	208	220	0
2	6	0.0497	0.192	0.052	175	208	220	0
3	9	0.0308	0.119	0.0322	175	208	220	0
3	24	0.0023	0.0839	0	400	510	600	1.03
4	9	0.0268	0.1037	0.0281	175	208	220	0
5	10	0.0228	0.0883	0.0239	175	208	220	0
6	10	0.0139	0.0605	2.459	175	193	200	0
7	8	0.0159	0.0614	0.0166	175	208	220	0
8	9	0.0427	0.1651	0.0447	175	208	220	0
8	10	0.0427	0.1651	0.0447	175	208	220	0
9	11	0.0023	0.0839	0	400	510	600	1.03
9	12	0.0023	0.0839	0	400	510	600	1.03
10	11	0.0023	0.0839	0	400	510	600	1.02
10	12	0.0023	0.0839	0	400	510	600	1.02
11	13	0.0061	0.0476	0.0999	500	600	625	0
11	14	0.0054	0.0418	0.0879	500	625	625	0
12	13	0.0061	0.0476	0.0999	500	625	625	0
12	23	0.0124	0.0966	0.203	500	625	625	0
13	23	0.0111	0.0865	0.1818	500	625	625	0
14	16	0.005	0.0389	0.0818	500	625	625	0
15	16	0.0022	0.0173	0.0364	500	600	625	0
15	21	0.0063	0.049	0.103	500	600	625	0
15	21	0.0063	0.049	0.103	500	600	625	0
15	24	0.0067	0.0519	0.1091	500	600	625	0
16	17	0.0033	0.0259	0.0545	500	600	625	0
16	19	0.003	0.0231	0.0485	500	600	625	0
17	18	0.0018	0.0144	0.0303	500	600	625	0
17	22	0.0135	0.1053	0.2212	500	600	625	0
18	21	0.0033	0.0259	0.0545	500	600	625	0
18	21	0.0033	0.0259	0.0545	500	600	625	0
19	20	0.0051	0.0396	0.0833	500	600	625	0
19	20	0.0051	0.0396	0.0833	500	600	625	0
20	23	0.0028	0.0216	0.0455	500	600	625	0
20	23	0.0028	0.0216	0.0455	500	600	625	0
21	22	0.0087	0.0678	0.1424	500	600	625	0

Generation Cost Data

In Table A.4 bus is the bus number, ε_1, ε_2 and ε_3 are the cost coefficient of thermal units.

Table A.4: Generation Cost data - RTS 24 Bus System

bus	ε_1	ε_2	ε_3
1	0.00	130.00	400.68
1	0.00	130.00	400.68
1	0.01	16.08	212.30
1	0.01	16.08	212.30
2	0.00	130.00	400.68
2	0.00	130.00	400.68
2	0.01	16.08	212.30
2	0.01	16.08	212.30
7	0.05	43.66	781.52
7	0.05	43.66	781.52
7	0.05	43.66	781.52
13	0.01	48.58	832.75
13	0.01	48.58	832.75
13	0.01	48.58	832.75
14	0.00	0.00	0.00
15	0.33	56.56	86.38
15	0.33	56.56	86.38
15	0.33	56.56	86.38
15	0.33	56.56	86.38
15	0.33	56.56	86.38
15	0.01	12.39	382.23
16	0.01	12.39	382.23
18	0.00	4.42	395.37
21	0.00	4.42	395.37
22	0.00	0.00	0.00
22	0.00	0.00	0.00
22	0.00	0.00	0.00
22	0.00	0.00	0.00
22	0.00	0.00	0.00
22	0.00	0.00	0.00
23	0.01	12.39	382.23
23	0.01	12.39	382.23
23	0.00	11.85	665.10

A.0.2 IEEE 118 Bus

The Modified IEEE 118 Bus Test System represents the Midwest American Electric Power System as of December, 1962 and is presented in Fig. A.2. This system has 118 bus, 54 generators, 99 loads, 14 shunts, 186 branches and 9 transformers on its base topology. Besides, the system has two voltage levels, 138 and 345 kV. The initial available generation capacity is 9966,2 MW while the initial system peak load is 6363 MW.

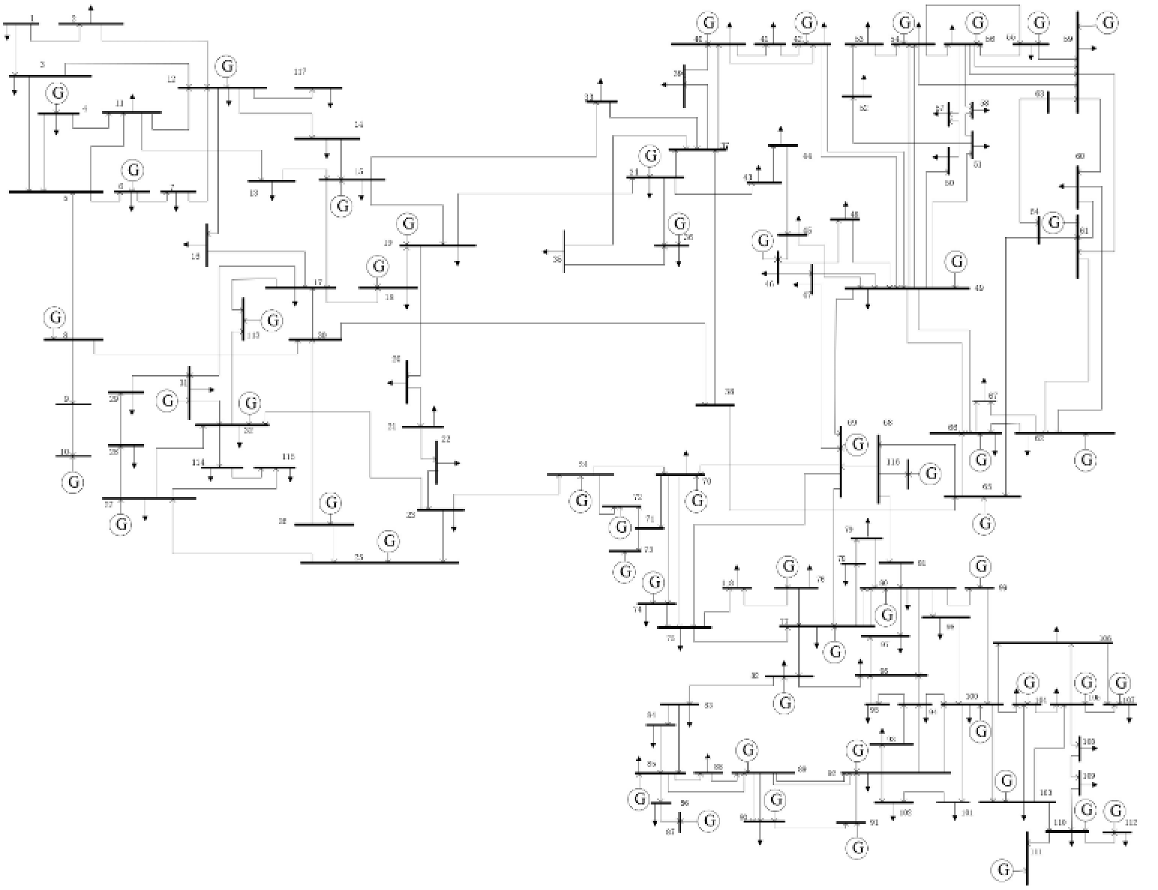

Figure A.2: IEEE 118 bus topology.

Bus Data

In Table A.5 the power base is 100 [MVA], bus is the bus number, $type$ is 1 for PQ, 2 for PV, 3 for reference bus and 4 for isolated buses. Pd and Qd are the real power demand and the reactive power demand (peak), Gs and Bs are the shunt conductance and the shunt susceptance (MW demanded and MVAr injected at V = 1.0 p.u), $area$ is the area number, $baseKV$ is the base voltage, $Vmax$ is the maximum voltage magnitude (p.u) and $Vmin$ is the minimum voltage magnitude.

Table A.5: Bus data - IEEE 118 Bus Syste,

bus	type	Pd	Qd	Gs	Bs	area	baseKV	Vmax	Vmin
1	2	51	27	0	0	1	138	1.1	0.9

Table A.5 continued from previous page

bus	type	Pd	Qd	Gs	Bs	area	baseKV	Vmax	Vmin
2	1	20	9	0	0	1	138	1.1	0.9
3	1	39	10	0	0	1	138	1.1	0.9
4	2	39	12	0	0	1	138	1.1	0.9
5	1	0	0	0	-40	1	138	1.1	0.9
6	2	52	22	0	0	1	138	1.1	0.9
7	1	19	2	0	0	1	138	1.1	0.9
8	2	28	0	0	0	1	345	1.1	0.9
9	1	0	0	0	0	1	345	1.1	0.9
10	2	0	0	0	0	1	345	1.1	0.9
11	1	70	23	0	0	1	138	1.1	0.9
12	2	47	10	0	0	1	138	1.1	0.9
13	1	34	16	0	0	1	138	1.1	0.9
14	1	14	1	0	0	1	138	1.1	0.9
15	2	90	30	0	0	1	138	1.1	0.9
16	1	25	10	0	0	1	138	1.1	0.9
17	1	11	3	0	0	1	138	1.1	0.9
18	2	60	34	0	0	1	138	1.1	0.9
19	2	45	25	0	0	1	138	1.1	0.9
20	1	18	3	0	0	1	138	1.1	0.9
21	1	14	8	0	0	1	138	1.1	0.9
22	1	10	5	0	0	1	138	1.1	0.9
23	1	7	3	0	0	1	138	1.1	0.9
24	2	13	0	0	0	1	138	1.1	0.9
25	2	0	0	0	0	1	138	1.1	0.9
26	2	0	0	0	0	1	345	1.1	0.9
27	2	71	13	0	0	1	138	1.1	0.9
28	1	17	7	0	0	1	138	1.1	0.9
29	1	24	4	0	0	1	138	1.1	0.9
30	1	0	0	0	0	1	345	1.1	0.9
31	2	43	27	0	0	1	138	1.1	0.9
32	2	59	23	0	0	1	138	1.1	0.9
33	1	23	9	0	0	1	138	1.1	0.9
34	2	59	26	0	14	1	138	1.1	0.9
35	1	33	9	0	0	1	138	1.1	0.9
36	2	31	17	0	0	1	138	1.1	0.9
37	1	0	0	0	-25	1	138	1.1	0.9
38	1	0	0	0	0	1	345	1.1	0.9
39	1	27	11	0	0	1	138	1.1	0.9
40	2	66	23	0	0	1	138	1.1	0.9
41	1	37	10	0	0	1	138	1.1	0.9
42	2	96	23	0	0	1	138	1.1	0.9
43	1	18	7	0	0	1	138	1.1	0.9
44	1	16	8	0	10	1	138	1.1	0.9
45	1	53	22	0	10	1	138	1.1	0.9

Table A.5 continued from previous page

bus	type	Pd	Qd	Gs	Bs	area	baseKV	Vmax	Vmin
46	2	28	10	0	10	1	138	1.1	0.9
47	1	34	0	0	0	1	138	1.1	0.9
48	1	20	11	0	15	1	138	1.1	0.9
49	2	87	30	0	0	1	138	1.1	0.9
50	1	17	4	0	0	1	138	1.1	0.9
51	1	17	8	0	0	1	138	1.1	0.9
52	1	18	5	0	0	1	138	1.1	0.9
53	1	23	11	0	0	1	138	1.1	0.9
54	2	113	32	0	0	1	138	1.1	0.9
55	2	63	22	0	0	1	138	1.1	0.9
56	2	84	18	0	0	1	138	1.1	0.9
57	1	12	3	0	0	1	138	1.1	0.9
58	1	12	3	0	0	1	138	1.1	0.9
59	2	277	113	0	0	1	138	1.1	0.9
60	1	78	3	0	0	1	138	1.1	0.9
61	2	0	0	0	0	1	138	1.1	0.9
62	2	77	14	0	0	1	138	1.1	0.9
63	1	0	0	0	0	1	345	1.1	0.9
64	1	0	0	0	0	1	345	1.1	0.9
65	2	0	0	0	0	1	345	1.1	0.9
66	2	39	18	0	0	1	138	1.1	0.9
67	1	28	7	0	0	1	138	1.1	0.9
68	1	0	0	0	0	1	345	1.1	0.9
69	3	0	0	0	0	1	138	1.1	0.9
70	2	66	20	0	0	1	138	1.1	0.9
71	1	0	0	0	0	1	138	1.1	0.9
72	2	12	0	0	0	1	138	1.1	0.9
73	2	6	0	0	0	1	138	1.1	0.9
74	2	68	27	0	12	1	138	1.1	0.9
75	1	47	11	0	0	1	138	1.1	0.9
76	2	68	36	0	0	1	138	1.1	0.9
77	2	61	28	0	0	1	138	1.1	0.9
78	1	71	26	0	0	1	138	1.1	0.9
79	1	39	32	0	20	1	138	1.1	0.9
80	2	130	26	0	0	1	138	1.1	0.9
81	1	0	0	0	0	1	345	1.1	0.9
82	1	54	27	0	20	1	138	1.1	0.9
83	1	20	10	0	10	1	138	1.1	0.9
84	1	11	7	0	0	1	138	1.1	0.9
85	2	24	15	0	0	1	138	1.1	0.9
86	1	21	10	0	0	1	138	1.1	0.9
87	2	0	0	0	0	1	138	1.1	0.9
88	1	48	10	0	0	1	138	1.1	0.9
89	2	0	0	0	0	1	138	1.1	0.9

Table A.5 continued from previous page

bus	type	Pd	Qd	Gs	Bs	area	baseKV	Vmax	Vmin
90	2	163	42	0	0	1	138	1.1	0.9
91	2	10	0	0	0	1	138	1.1	0.9
92	2	65	10	0	0	1	138	1.1	0.9
93	1	12	7	0	0	1	138	1.1	0.9
94	1	30	16	0	0	1	138	1.1	0.9
95	1	42	31	0	0	1	138	1.1	0.9
96	1	38	15	0	0	1	138	1.1	0.9
97	1	15	9	0	0	1	138	1.1	0.9
98	1	34	8	0	0	1	138	1.1	0.9
99	2	42	0	0	0	1	138	1.1	0.9
100	2	37	18	0	0	1	138	1.1	0.9
101	1	22	15	0	0	1	138	1.1	0.9
102	1	5	3	0	0	1	138	1.1	0.9
103	2	23	16	0	0	1	138	1.1	0.9
104	2	38	25	0	0	1	138	1.1	0.9
105	2	31	26	0	20	1	138	1.1	0.9
106	1	43	16	0	0	1	138	1.1	0.9
107	2	50	12	0	6	1	138	1.1	0.9
108	1	2	1	0	0	1	138	1.1	0.9
109	1	8	3	0	0	1	138	1.1	0.9
110	2	39	30	0	6	1	138	1.1	0.9
111	2	0	0	0	0	1	138	1.1	0.9
112	2	68	13	0	0	1	138	1.1	0.9
113	2	6	0	0	0	1	138	1.1	0.9
114	1	8	3	0	0	1	138	1.1	0.9
115	1	22	7	0	0	1	138	1.1	0.9
116	2	184	0	0	0	1	138	1.1	0.9
117	1	20	8	0	0	1	138	1.1	0.9
118	1	33	15	0	0	1	138	1.1	0.9

Generation Data

In Table A.6, $GenNumber$ is the number of the generator, bus is the bus number, Pg is the real power output (MW), Qg is the reactive power output (MVAr), $Qmax$ is the maximum reactive power output (MVAr), $Qmin$ is the minimum reactive power output (MVAr), Vg is the voltage magnitude set point (p.u.), $mBase$ is the total MVA base of machine (defaults to power base), $status$ is the machine status (1 for in-service and 0 for out-of-service), $Pmax$ is the maximum real power output (MW) and FOR is the forced outage rate.

Table A.6: Generation data - IEEE 118 Bus System

Gen Number	Bus	Pg	Qg	Qmax	Qmin	Vg	mBase	Status	Pmax	FOR
1	1	0	0	7.5	-2.5	0.955	100	1	100	0.10

Table A.6 continued from previous page

Gen Number	Bus	Pg	Qg	Qmax	Qmin	Vg	mBase	Status	Pmax	FOR
2	4	0	0	150	-150	0.998	100	1	100	0.10
3	6	0	0	25	-6.5	0.99	100	1	100	0.04
4	8	0	0	150	-150	1.015	100	1	100	0.03
5	10	225	0	100	-73.5	1.05	100	1	550	0.02
6	12	42.5	0	60	-17.5	0.99	100	1	185	0.08
7	15	0	0	15	-5	0.97	100	1	100	0.08
8	18	0	0	25	-8	0.973	100	1	100	0.02
9	19	0	0	12	-4	0.962	100	1	100	0.05
10	24	0	0	150	-150	0.992	100	1	100	0.01
11	25	110	0	70	-23.5	1.05	100	1	320	0.07
12	26	157	0	500	-500	1.015	100	1	414	0.08
13	27	0	0	150	-150	0.968	100	1	100	0.09
14	31	3.5	0	150	-150	0.967	100	1	107	0.08
15	32	0	0	21	-7	0.963	100	1	100	0.05
16	34	0	0	12	-4	0.984	100	1	100	0.04
17	36	0	0	12	-4	0.98	100	1	100	0.01
18	40	0	0	150	-150	0.97	100	1	100	0.09
19	42	0	0	150	-150	0.985	100	1	100	0.02
20	46	9.5	0	50	-50	1.005	100	1	119	0.01
21	49	102	0	105	-42.5	1.025	100	1	304	0.03
22	54	24	0	150	-150	0.955	100	1	148	0.10
23	55	0	0	11.5	-4	0.952	100	1	100	0.07
24	56	0	0	7.5	-4	0.954	100	1	100	0.04
25	59	77.5	0	90	-30	0.985	100	1	255	0.09
26	61	80	0	150	-50	0.995	100	1	260	0.07
27	62	0	0	10	-10	0.998	100	1	100	0.07
28	65	195.5	0	100	-33.5	1.005	100	1	491	0.05
29	66	196	0	100	-33.5	1.05	100	1	492	0.10
30	69	258.2	0	150	-150	1.035	100	1	805.2	0.09
31	70	0	0	16	-5	0.984	100	1	100	0.01
32	72	0	0	50	-50	0.98	100	1	100	0.02
33	73	0	0	50	-50	0.991	100	1	100	0.05
34	74	0	0	4.5	-3	0.958	100	1	100	0.06
35	76	0	0	11.5	-4	0.943	100	1	100	0.03
36	77	0	0	35	-10	1.006	100	1	100	0.05
37	80	238.5	0	140	-82.5	1.04	100	1	577	0.04
38	85	0	0	11.5	-4	0.985	100	1	100	0.02
39	87	2	0	500	-50	1.015	100	1	104	0.10
40	89	303.5	0	150	-105	1.005	100	1	707	0.04
41	90	0	0	150	-150	0.985	100	1	100	0.09
42	91	0	0	50	-50	0.98	100	1	100	0.01
43	92	0	0	4.5	-1.5	0.99	100	1	100	0.05
44	99	0	0	50	-50	1.01	100	1	100	0.01

Table A.6 continued from previous page

Gen Number	Bus	Pg	Qg	Qmax	Qmin	Vg	mBase	Status	Pmax	FOR
45	100	126	0	77.5	-25	1.017	100	1	352	0.04
46	103	20	0	20	-7.5	1.01	100	1	140	0.10
47	104	0	0	11.5	-4	0.971	100	1	100	0.09
48	105	0	0	11.5	-4	0.965	100	1	100	0.02
49	107	0	0	100	-100	0.952	100	1	100	0.06
50	110	0	0	11.5	-4	0.973	100	1	100	0.03
51	111	18	0	500	-50	0.98	100	1	136	0.10
52	112	0	0	500	-50	0.975	100	1	100	0.01
53	113	0	0	100	-50	0.993	100	1	100	0.08
54	116	0	0	500	-500	1.005	100	1	100	0.02

Branch Data

In Table A.7, $fbus$ is the “from” bus number and $tbus$ is the “to” bus number, r is the resistance (p.u.), x is the reactance (p.u.), b is the total line charging susceptance (p.u.), $rateA$ is the MVA rating A (long term rating), $rateB$ is the MVA rating B (short term rating), $rateC$ is the MVA rating C (emergency rating), $ratio$ is the transformer off nominal turns ratio and FOR is the forced outage rate.

Table A.7: Branch data - IEEE 118 Bus System

fbus	tbus	r	x	B	rateA	rateB	rateC	ratio	FOR
1	2	0.0303	0.0999	0.0254	100	125	156.25	0	0.05
1	3	0.0129	0.0424	0.01082	100	125	156.25	0	0.03
4	5	0.00176	0.00798	0.0021	500	625	781.25	0	0.01
3	5	0.0241	0.108	0.0284	100	125	156.25	0	0.03
5	6	0.0119	0.054	0.01426	100	125	156.25	0	0.05
6	7	0.00459	0.0208	0.0055	100	125	156.25	0	0.05
8	9	0.00244	0.0305	1.162	500	625	781.25	0	0.02
8	5	0	0.0267	0	500	625	781.25	0.985	0.02
9	10	0.00258	0.0322	1.23	500	625	781.25	0	0.05
4	11	0.0209	0.0688	0.01748	100	125	156.25	0	0.03
5	11	0.0203	0.0682	0.01738	100	125	156.25	0	0.03
11	12	0.00595	0.0196	0.00502	100	125	156.25	0	0.01
2	12	0.0187	0.0616	0.01572	100	125	156.25	0	0.01
3	12	0.0484	0.16	0.0406	100	125	156.25	0	0.05
7	12	0.00862	0.034	0.00874	100	125	156.25	0	0.05
11	13	0.02225	0.0731	0.01876	100	125	156.25	0	0.02
12	14	0.0215	0.0707	0.01816	100	125	156.25	0	0.05
13	15	0.0744	0.2444	0.06268	100	125	156.25	0	0.05
14	15	0.0595	0.195	0.0502	100	125	156.25	0	0.05
12	16	0.0212	0.0834	0.0214	100	125	156.25	0	0.05
15	17	0.0132	0.0437	0.0444	500	625	781.25	0	0.04
16	17	0.0454	0.1801	0.0466	100	125	156.25	0	0.01

Table A.7 continued from previous page

fbus	tbus	r	x	B	rateA	rateB	rateC	ratio	FOR
17	18	0.0123	0.0505	0.01298	100	125	156.25	0	0.02
18	19	0.01119	0.0493	0.01142	100	125	156.25	0	0.03
19	20	0.0252	0.117	0.0298	100	125	156.25	0	0.01
15	19	0.012	0.0394	0.0101	100	125	156.25	0	0.02
20	21	0.0183	0.0849	0.0216	100	125	156.25	0	0.05
21	22	0.0209	0.097	0.0246	100	125	156.25	0	0.02
22	23	0.0342	0.159	0.0404	100	125	156.25	0	0.03
23	24	0.0135	0.0492	0.0498	100	125	156.25	0	0.04
23	25	0.0156	0.08	0.0864	500	625	781.25	0	0.05
26	25	0	0.0382	0	500	625	781.25	0.96	0.02
25	27	0.0318	0.163	0.1764	500	625	781.25	0	0.04
27	28	0.01913	0.0855	0.0216	100	125	156.25	0	0.02
28	29	0.0237	0.0943	0.0238	100	125	156.25	0	0.01
30	17	0	0.0388	0	500	625	781.25	0.96	0.04
8	30	0.00431	0.0504	0.514	100	125	156.25	0	0.04
26	30	0.00799	0.086	0.908	500	625	781.25	0	0.02
17	31	0.0474	0.1563	0.0399	100	125	156.25	0	0.03
29	31	0.0108	0.0331	0.0083	100	125	156.25	0	0.02
23	32	0.0317	0.1153	0.1173	100	125	156.25	0	0.05
31	32	0.0298	0.0985	0.0251	100	125	156.25	0	0.02
27	32	0.0229	0.0755	0.01926	100	125	156.25	0	0.04
15	33	0.038	0.1244	0.03194	100	125	156.25	0	0.04
19	34	0.0752	0.247	0.0632	100	125	156.25	0	0.05
35	36	0.00224	0.0102	0.00268	100	125	156.25	0	0.02
35	37	0.011	0.0497	0.01318	100	125	156.25	0	0.03
33	37	0.0415	0.142	0.0366	100	125	156.25	0	0.01
34	36	0.00871	0.0268	0.00568	100	125	156.25	0	0.03
34	37	0.00256	0.0094	0.00984	500	625	781.25	0	0.05
38	37	0	0.0375	0	500	625	781.25	0.935	0.01
37	39	0.0321	0.106	0.027	100	125	156.25	0	0.02
37	40	0.0593	0.168	0.042	100	125	156.25	0	0.04
30	38	0.00464	0.054	0.422	100	125	156.25	0	0.05
39	40	0.0184	0.0605	0.01552	100	125	156.25	0	0.03
40	41	0.0145	0.0487	0.01222	100	125	156.25	0	0.05
40	42	0.0555	0.183	0.0466	100	125	156.25	0	0.03
41	42	0.041	0.135	0.0344	100	125	156.25	0	0.02
43	44	0.0608	0.2454	0.06068	100	125	156.25	0	0.03
34	43	0.0413	0.1681	0.04226	100	125	156.25	0	0.01
44	45	0.0224	0.0901	0.0224	100	125	156.25	0	0.01
45	46	0.04	0.1356	0.0332	100	125	156.25	0	0.02
46	47	0.038	0.127	0.0316	100	125	156.25	0	0.04
46	48	0.0601	0.189	0.0472	100	125	156.25	0	0.04
47	49	0.0191	0.0625	0.01604	100	125	156.25	0	0.05
42	49	0.0715	0.323	0.086	100	125	156.25	0	0.04

Table A.7 continued from previous page

fbus	tbus	r	x	B	rateA	rateB	rateC	ratio	FOR
42	49	0.0715	0.323	0.086	100	125	156.25	0	0.04
45	49	0.0684	0.186	0.0444	100	125	156.25	0	0.03
48	49	0.0179	0.0505	0.01258	100	125	156.25	0	0.02
49	50	0.0267	0.0752	0.01874	100	125	156.25	0	0.04
49	51	0.0486	0.137	0.0342	100	125	156.25	0	0.01
51	52	0.0203	0.0588	0.01396	100	125	156.25	0	0.01
52	53	0.0405	0.1635	0.04058	100	125	156.25	0	0.04
53	54	0.0263	0.122	0.031	100	125	156.25	0	0.02
49	54	0.073	0.289	0.0738	100	125	156.25	0	0.03
49	54	0.0869	0.291	0.073	100	125	156.25	0	0.03
54	55	0.0169	0.0707	0.0202	100	125	156.25	0	0.04
54	56	0.00275	0.00955	0.00732	100	125	156.25	0	0.02
55	56	0.00488	0.0151	0.00374	100	125	156.25	0	0.04
56	57	0.0343	0.0966	0.0242	100	125	156.25	0	0.05
50	57	0.0474	0.134	0.0332	100	125	156.25	0	0.01
56	58	0.0343	0.0966	0.0242	100	125	156.25	0	0.03
51	58	0.0255	0.0719	0.01788	100	125	156.25	0	0.01
54	59	0.0503	0.2293	0.0598	100	125	156.25	0	0.04
56	59	0.0825	0.251	0.0569	100	125	156.25	0	0.05
56	59	0.0803	0.239	0.0536	100	125	156.25	0	0.05
55	59	0.04739	0.2158	0.05646	100	125	156.25	0	0.03
59	60	0.0317	0.145	0.0376	100	125	156.25	0	0.03
59	61	0.0328	0.15	0.0388	100	125	156.25	0	0.04
60	61	0.00264	0.0135	0.01456	500	625	781.25	0	0.02
60	62	0.0123	0.0561	0.01468	100	125	156.25	0	0.04
61	62	0.00824	0.0376	0.0098	100	125	156.25	0	0.01
63	59	0	0.0386	0	500	625	781.25	0.96	0.04
63	64	0.00172	0.02	0.216	500	625	781.25	0	0.04
64	61	0	0.0268	0	500	625	781.25	0.985	0.03
38	65	0.00901	0.0986	1.046	500	625	781.25	0	0.01
64	65	0.00269	0.0302	0.38	500	625	781.25	0	0.03
49	66	0.018	0.0919	0.0248	500	625	781.25	0	0.03
49	66	0.018	0.0919	0.0248	500	625	781.25	0	0.03
62	66	0.0482	0.218	0.0578	100	125	156.25	0	0.05
62	67	0.0258	0.117	0.031	100	125	156.25	0	0.01
65	66	0	0.037	0	500	625	781.25	0.935	0.02
66	67	0.0224	0.1015	0.02682	100	125	156.25	0	0.05
65	68	0.00138	0.016	0.638	500	625	781.25	0	0.04
47	69	0.0844	0.2778	0.07092	100	125	156.25	0	0.04
49	69	0.0985	0.324	0.0828	100	125	156.25	0	0.05
68	69	0	0.037	0	500	625	781.25	0.935	0.01
69	70	0.03	0.127	0.122	500	625	781.25	0	0.03
24	70	0.00221	0.4115	0.10198	100	125	156.25	0	0.04
70	71	0.00882	0.0355	0.00878	100	125	156.25	0	0.01

Table A.7 continued from previous page

fbus	tbus	r	x	B	rateA	rateB	rateC	ratio	FOR
24	72	0.0488	0.196	0.0488	100	125	156.25	0	0.04
71	72	0.0446	0.18	0.04444	100	125	156.25	0	0.02
71	73	0.00866	0.0454	0.01178	100	125	156.25	0	0.05
70	74	0.0401	0.1323	0.03368	100	125	156.25	0	0.05
70	75	0.0428	0.141	0.036	100	125	156.25	0	0.03
69	75	0.0405	0.122	0.124	500	625	781.25	0	0.02
74	75	0.0123	0.0406	0.01034	100	125	156.25	0	0.05
76	77	0.0444	0.148	0.0368	100	125	156.25	0	0.01
69	77	0.0309	0.101	0.1038	100	125	156.25	0	0.02
75	77	0.0601	0.1999	0.04978	100	125	156.25	0	0.03
77	78	0.00376	0.0124	0.01264	100	125	156.25	0	0.04
78	79	0.00546	0.0244	0.00648	100	125	156.25	0	0.01
77	80	0.017	0.0485	0.0472	500	625	781.25	0	0.01
77	80	0.0294	0.105	0.0228	500	625	781.25	0	0.01
79	80	0.0156	0.0704	0.0187	100	125	156.25	0	0.02
68	81	0.00175	0.0202	0.808	500	625	781.25	0	0.01
81	80	0	0.037	0	500	625	781.25	0.935	0.01
77	82	0.0298	0.0853	0.08174	100	125	156.25	0	0.01
82	83	0.0112	0.03665	0.03796	100	125	156.25	0	0.03
83	84	0.0625	0.132	0.0258	100	125	156.25	0	0.05
83	85	0.043	0.148	0.0348	100	125	156.25	0	0.04
84	85	0.0302	0.0641	0.01234	100	125	156.25	0	0.01
85	86	0.035	0.123	0.0276	500	625	781.25	0	0.01
86	87	0.02828	0.2074	0.0445	500	625	781.25	0	0.04
85	88	0.02	0.102	0.0276	100	125	156.25	0	0.03
85	89	0.0239	0.173	0.047	100	125	156.25	0	0.03
88	89	0.0139	0.0712	0.01934	500	625	781.25	0	0.02
89	90	0.0518	0.188	0.0528	500	625	781.25	0	0.02
89	90	0.0238	0.0997	0.106	500	625	781.25	0	0.02
90	91	0.0254	0.0836	0.0214	100	125	156.25	0	0.03
89	92	0.0099	0.0505	0.0548	500	625	781.25	0	0.04
89	92	0.0393	0.1581	0.0414	500	625	781.25	0	0.01
91	92	0.0387	0.1272	0.03268	100	125	156.25	0	0.01
92	93	0.0258	0.0848	0.0218	100	125	156.25	0	0.02
92	94	0.0481	0.158	0.0406	100	125	156.25	0	0.03
93	94	0.0223	0.0732	0.01876	100	125	156.25	0	0.04
94	95	0.0132	0.0434	0.0111	100	125	156.25	0	0.05
80	96	0.0356	0.182	0.0494	100	125	156.25	0	0.01
82	96	0.0162	0.053	0.0544	100	125	156.25	0	0.01
94	96	0.0269	0.0869	0.023	100	125	156.25	0	0.03
80	97	0.0183	0.0934	0.0254	100	125	156.25	0	0.02
80	98	0.0238	0.108	0.0286	100	125	156.25	0	0.01
80	99	0.0454	0.206	0.0546	100	125	156.25	0	0.05
92	100	0.0648	0.295	0.0472	100	125	156.25	0	0.02

Table A.7 continued from previous page

fbus	tbus	r	x	B	rateA	rateB	rateC	ratio	FOR
94	100	0.0178	0.058	0.0604	100	125	156.25	0	0.04
95	96	0.0171	0.0547	0.01474	100	125	156.25	0	0.03
96	97	0.0173	0.0885	0.024	100	125	156.25	0	0.01
98	100	0.0397	0.179	0.0476	100	125	156.25	0	0.04
99	100	0.018	0.0813	0.0216	100	125	156.25	0	0.02
100	101	0.0277	0.1262	0.0328	100	125	156.25	0	0.02
92	102	0.0123	0.0559	0.01464	100	125	156.25	0	0.03
101	102	0.0246	0.112	0.0294	100	125	156.25	0	0.04
100	103	0.016	0.0525	0.0536	500	625	781.25	0	0.05
100	104	0.0451	0.204	0.0541	100	125	156.25	0	0.03
103	104	0.0466	0.1584	0.0407	100	125	156.25	0	0.01
103	105	0.0535	0.1625	0.0408	100	125	156.25	0	0.04
100	106	0.0605	0.229	0.062	100	125	156.25	0	0.02
104	105	0.00994	0.0378	0.00986	100	125	156.25	0	0.05
105	106	0.014	0.0547	0.01434	100	125	156.25	0	0.04
105	107	0.053	0.183	0.0472	100	125	156.25	0	0.04
105	108	0.0261	0.0703	0.01844	100	125	156.25	0	0.02
106	107	0.053	0.183	0.0472	100	125	156.25	0	0.01
108	109	0.0105	0.0288	0.0076	100	125	156.25	0	0.05
103	110	0.03906	0.1813	0.0461	100	125	156.25	0	0.04
109	110	0.0278	0.0762	0.0202	100	125	156.25	0	0.02
110	111	0.022	0.0755	0.02	100	125	156.25	0	0.01
110	112	0.0247	0.064	0.062	100	125	156.25	0	0.02
17	113	0.00913	0.0301	0.00768	100	125	156.25	0	0.05
32	113	0.0615	0.203	0.0518	500	625	781.25	0	0.02
32	114	0.0135	0.0612	0.01628	100	125	156.25	0	0.03
27	115	0.0164	0.0741	0.01972	100	125	156.25	0	0.05
114	115	0.0023	0.0104	0.00276	100	125	156.25	0	0.01
68	116	0.00034	0.00405	0.164	500	625	781.25	0	0.03
12	117	0.0329	0.14	0.0358	100	125	156.25	0	0.04
75	118	0.0145	0.0481	0.01198	100	125	156.25	0	0.03
76	118	0.0164	0.0544	0.01356	100	125	156.25	0	0.04

Appendix B

Main papers published during the Ph.D. Course

B.0.1 - *Static transmission expansion planning using heuristic and metaheuristic techniques*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE PowerTech, Eindhoven, June 2015.

B.0.2 - *Multiyear and multi-criteria ac transmission expansion planning model considering reliability and investment costs*. Phillipe Vilaça Gomes, João Silva and João Tomé Saraiva, in Proceedings of IEEE EEM, Porto, June 2016.

B.0.3 - *Evaluation of the performance of space reduction technique using ac and dc models in transmission expansion problems*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE EEM, Porto, June 2016.

B.0.4 - *Hybrid discrete evolutionary pso for ac dynamic transmission expansion planning*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE ENERGYCON, Leuven, April 2016.

B.0.5 - *Hybrid genetic algorithm for multi-objective transmission expansion planning*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE ENERGYCON, Leuven, April 2016.

B.0.6 - *Transmission system planning considering solar distributed generation penetration*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE EEM, Dresden, June 2017.

B.0.7 - *Multiyear transmission expansion planning under hydrological uncertainty*. Phillipe Vilaça Gomes and João Tomé Saraiva, in Proceedings of IEEE PowerTech, Manchester, June 2017.

B.0.8 - *Impact of Large Fleets of Plug-in-Electric Vehicles on Transmission Systems Expansion Planning*. Phillipe Vilaça Gomes, João Tomé Saraiva, Mario Coelho, Bruno Dias, Leonardo Willer and Candiá Junior, in Proceedings of PSCC, Dublin, June 2018.

B.0.9 - *A novel efficient method for multiyear multiobjective dynamic transmission system planning*. Phillipe Vilaça Gomes and João Tomé Saraiva, International Journal of Electrical Power & Energy Systems, 100:10–18, 2018.

B.0.10 - *Technical-economic analysis for the integration of PV systems in Brazil considering policy and regulatory issues*. Phillipe Vilaça Gomes, Nelson Knak, Leonel Carvalho, Jean Sumaili, João Tomé Saraiva, Bruno Dias, Vladimiro Miranda and Suzana Menezes de Souza, Energy Policy, 199-206, 2018.

B.0.1 Static transmission expansion planning using heuristic and meta-heuristic techniques. (IEEE Powertech, 2015)

Static Transmission Expansion Planning using Heuristic and Metaheuristic Techniques

Phillipe Vilaça Gomes
INESC TEC and FEUP/DEEC
Dept. Eng. Eletrotécnica e Computadores da Faculdade de Engenharia da Universidade do Porto
Porto, Portugal
pvgomes@inescporto.pt

João Tomé Saraiva
INESC TEC and FEUP/DEEC
Dept. Eng. Eletrotécnica e Computadores da Faculdade de Engenharia da Universidade do Porto
Porto, Portugal
jsaraiva@fe.up.pt

***Abstract* — This paper describes a hybrid tool to perform Static Transmission Expansion Planning, STEP, studies and its application to the Garver6-Bus academic system and to the Southern Brazilian Transmission equivalent real system. The developed STEP tool integrates two phases as follows. The first one uses Constructive Heuristic Algorithms (CHA) to reduce the search space, and the second uses Particle Swarm Optimization (PSO) to identify the final solution. This hybridization between CHAs and PSO proved to be very effective and shows good performance to reduce the size of the STEP search space and to identify good quality solutions. These are relevant issues given the combinatorial nature of investment problems leading to the explosion of the number of alternative plans, one of the greatest difficulties faced in this planning problem.**

***Index Terms* — Constructive Heuristic Algorithms, Particle Swarm Optimization, Reduction of the Search Space Size, Transmission Expansion Planning.**

I. INTRODUCTION

The purpose of STEP, Static Transmission Expansion Planning problems, is to determine how the transmission capacity of a network should be enlarged, satisfying the increasing demand, i.e, from a pre-existing list of candidate circuits to be built, identify those that will be constructed to minimize the operation cost of the system while supplying the forecasted demand along a planning horizon [1]. The increasing demand implies modifying the system over time so that the load is properly supplied. There are usually different alternatives to do this that include not only building new transmission lines but also installing new generation facilities closer to the demand centers. In whatever way, it is frequently not economically feasible or even possible to build generating units near the demand centers. On the other hand, transmission expansion can also enable the optimal dispatch of power plants, because having a stronger transmission system provides more flexibility to dispatch generation apart from improving the reliability of the system and decreasing the likelihood of having congested branches.

Solving the STEP optimization problem is an arduous task since it has some special features that increase its complexity:

- The search space is non-convex so that several solution algorithms may converge to local optima;
- In some cases there are isolated smaller systems;
- The problem typically has an integer nature leading to the combinatorial explosion of investment alternative plans that can be devised. This requires a high computational effort to identify good quality plans.

These characteristics correspond to the main difficulties in developing high-performance tools in terms of speed, efficiency and robustness to solve the STEP problem [2]. The literature of this area includes a variety of models and tools to solve the STEP and to address the difficulties mentioned above. These models and tools can be organized as follows:

- Classical Optimization Algorithms
  They use decomposition techniques and generally find global optimal solutions for a relaxed version of the original integer problem in which integer investment alternatives are substituted by continuous variables. However, they usually require a large computational effort and therefore they display difficulties to address the expansion of medium and large systems as most of real transmission systems are. In some cases they can also show convergence problems as detailed in [3], [4];
- Constructive Heuristics Algorithms (CHAs)
  These approaches correspond to simplified procedures that are suitable to identify feasible solutions for complex problems using efficient and easily applied algorithms. They have little computational effort, but they rarely find the optimal global solution, especially if one is addressing real transmission networks [5] , [6];
- Metaheuristics
  They are heuristic techniques that are enhanced with particular search procedures in most cases inspired in natural mechanisms. They are especially suited to solve complex and combinatorial problems usually identifying optimal or suboptimal solutions even for large systems.

CAPES Foundation, Ministry of Education of Brazil.

However, they are typically associated to large computational efforts [7].

Given the shortcomings of the above approaches, this paper details the application of an hybridizing methodology to solve the STEP problem. This hybridization results in an algorithm that incorporates two phases. The first phase is termed *The reduction of search space size* and it uses two CHAs with different modeling of the problem: the Garver CHA and the Minimum Effort CHA. In the second phase, termed as *The refinement of the solution*, we used Particle Swarm Optimization (PSO) to search for the global optimum solution in the reduced search space, that is, in the output of the first phase. This process was designed to overcome the problem associated to large computational effort that is typical to metaheuristics. Accordingly, we promote a reduction of the search space and only afterwards PSO is used to search for the most adequate solution in the reduced solution space.

Regarding the structure of the paper, following the introduction already presented, Section II refers to the mathematical model for TEP problem, Section III details the CHA theory, Section IV provides a brief presentation of the PSO approach and the hybridization of these two approaches in the context of the STEP problem. Section V presents the results of PSO and hybrid tool applied to the Garver-6-bus and to the Equivalent System Southern Brazil test systems as well as the considerations adopted for these simulations. Finally, Section VI discusses the results of the simulations, as well as the behavior of the proposed tool and presents the main conclusions of this paper.

II. MATHEMATICAL MODELING OF THE STEP PROBLEM

The complete mathematical model for the STEP problem uses the AC model for the operation of the power system as described in [8]. However, this model has many obstacles to its widespread use. One possible simplification results from only addressing active power flows in the STEP problem leaving the reactive planning issues to a subsequent phase. Another problem is related with the presence of sets of islanded buses in the starting configuration. Accordingly, most of the STEP models are based on relaxed versions of the full AC version. Such models are the Transportation Model, the DC Model and Hybrid Models. The developed approach incorporates two CHAs in phase 1, the Garver and the Minimum Effort CHA. These two CHAs use the Transportation Model and the DC Model, respectively. The formulation based on the DC model is detailed below [9] .

$$\text{minimize } v = \sum_{(i,j)} c_{ij} n_{ij} + \alpha . \sum r_k \quad (1)$$

$$\text{subject to } \quad S.f + g + r = d \quad (2)$$

$$f_{ij} - \left(\gamma_{ij}^0 + x_{ij}\right)\left(\theta_i - \theta_j\right) = 0 \quad (3)$$

$$\left|f_{ij}\right| \le \left(x_{ij} + \gamma_{ij}^0\right)\overline{\phi}_{ij} \quad (4)$$

$$0 \le g_i \le \overline{g}_i \quad (5)$$

$$0 \le \eta_{ij} \le \overline{\eta}_{ij}$$

Regarding the nature of the variables, η_{ij} integer, x_{ij} discrete, and f_{ij} and θ_i are unrestricted. On the other hand, c_{ij} is the cost of a circuit ij, η_{ij} is the number of circuits to be built from i to j, α is a factor that penalizes load shedding in the bus k modelled by r_k , S is the transposed incidence node-branch matrix of the power system, f is the vector of the branch flows, g is the generation vector, d is the demand vector, γ_{ij}^0 is the equivalent susceptance of circuit i-j in the base topology, x_{ij} is the susceptance of the added i-j circuit, θ is the voltage angle, and finally $\phi_{ij} = \overline{f_{ij}} / \gamma_{ij}$.

The Transportation Model differs from the DC based Model because it does not use the second Kirchhoff law, i.e, the equality constraints (3). These models are usually known as the *associated problems* to the STEP problem.

The size of the search space (S) of STEP problem can be calculated taking into account the maximum number of circuits that can be built into candidates routes (n) and the number of existing candidate routes (p), as shown in (7).

$$S = (n+1)^p \quad (7)$$

III. CONSTRUCTIVE HEURISTIC ALGORITHMS

These algorithms analyze the search space using a number of *sensitivity criteria* interpreted as quantifiers used to evaluate how the system performs if some lines are added to the original system. Therefore, in each step a circuit is selected and tested and it is eventually selected to remain in the reduced search space. The sensitivity criteria correspond to parameters that measure how the objective function of the problem changes if a circuit is added. It is then clear that they should be able to identify the most attractive circuits to be added, and correspond to indicators having a local character. However, they do not ensure that the CHA reduces the search space in a way that the global optimum is included in it. The generic CHA is shown in Fig. 1 bellow. In the developed approach, this tool was used in an auxiliary way, i.e, its output is used just to reduce the search space.

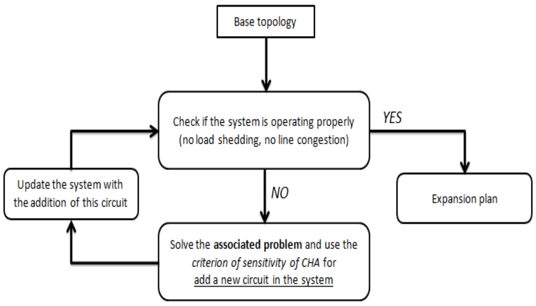

Figure 1. Illustration of a generic CHA

The Garver CHA uses the Transportation Model to solve the STEP problem and uses as criterion the sensitivity of the flows associated to the new circuits that can be added to the system. This sensitivity is modeled by (8) as defined in [3].

The search reduction promoted by this CHA may not be the most interesting (compared to the one obtained with Minimum Effort approach) because it uses the Transportation Model. However, the literature indicates that it outputs acceptable results for complex and islanded systems.

$$CS^{G} = n_{ij} \cdot \overline{f_{ij}} \tag{8}$$

The Minimum Effort CHA uses the DC Model as an associated problem and its sensitivity criterion is given by (9) as detailed in [5]. This approach is more refined than the previous one and therefore it usually provides better results, but it presents difficulties in dealing with islanded systems. This can be addressed by creating a fictitious network overlaid with the existing one connecting the entire system. However, even using this artificial mechanism, the Minimum Effort CHA can display convergence problems in some cases.

$$CS^{ME} = \frac{1}{2} \cdot (\theta_i - \theta_j)^2 \cdot \gamma_{ij} \tag{9}$$

As the Garver CHA is a relaxed technique, it displays fewer convergence problems to get a reduction of the search space. However, the Minimum Effort CHA models real problems in a closer way and therefore it can provide better answers, in most cases. So, it seems advantageous to combine these two techniques in order to build a reduced search space profiting from the characteristics of both approaches. Accordingly, the output of the first phase of the developed algorithm to solve the STEP problem (*reduction of the search space size*) corresponds to the union of the search spaces that are obtained using these two CHAs.

IV. PARTICLE SWARM OPTIMIZATION – PSO

PSO is a swarm intelligence technique and a stochastic optimization algorithm based on social simulation models. The development of PSO was based on concepts which govern socially organized populations in nature, such as bird flocks, fish schools and animal herds [10]. This technique basically employs a set of points (population) that moves in the search space. The best position reached by each point is maintained, and then communicated to all particles of the swarm. Each of these particles is characterized by a value that measures the suitability of the particle as a solution to the problem. Each particle evolves along the solution algorithm using a velocity vector that defines the direction of its movement. The swarm is successful over time because the position of each particle is updated, taking into account the best position of the particle in the past generations and the best position of all particles in the swarm. The velocity of each particle is given by (10) and the position is obtained by (11).

$$V_i^{k+1} = wv_i^k + c_1.rand_1.(pbest_i - s_i^k) + c_2.rand_2.(gbest_i - s_i^k) \tag{10}$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{11}$$

In this expression V_i^k is the velocity of particle i at iteration k, w is a weighting function, c_1 and c_2 are weighting coefficients, rand is a random number in $[0,1]$, *pbest* is the best particle in previous generations, s_i^k is the position of particle i at iteration k and *gbest* is the best particle in the entire swarm. This movement rule is illustrated in Fig. 2.

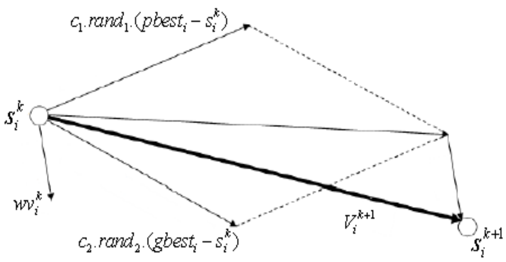

Figure 2. Movement rule of the PSO algorithm.

The stopping criterion is usually given by a function that establishing a maximum or a minimum range for the evolution of PSO parameters or a maximum number of iterations. Regarding expression (10) the first term wv_i^k refers to the moment of inertia of the particle. The second term $c_1.rand_1.(pbest - s_i^k)$ refers to the "cognitive" part, which represents the individual knowledge of the particle acquired over the search process. The third term $c_2.rand_2.(gbest_i - s_i^k)$ refers to the "social" part, which is the collaboration between the particles, i.e, the collective knowledge gained from the swarm throughout the search process. The second and third terms are weighted by two constants (c_1 and c_2) that represent the weighting of the individual and collective components respectively and influence each particle towards the new solution, while the first term is weighted by a function (w), called inertial weighting function, that induces the particle to move in a direction based on the move of the previous iteration. Larger values of the weighting function facilitate a global search while smaller values tend to represent a local one. Results provided in the literature mention that it is better to adjust the weighting function in a larger value at the beginning of the search process, promoting a more comprehensive search, and gradually, throughout the process, reduce it to refine the search [11]. Therefore, in the developed approach we used for w values of 0.9 ($w_{\max}$) in the beginning of the process and of 0.4 ($w_{\min}$) in the end of the process in accordance with (12). In this expression $iteration_{\max}$ is the maximum number of iterations allowed in the process and $iteration$ represents the current iteration.

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iteration_{\max}}.iteration \tag{12}$$

The PSO tool was used in this approach as an auxiliary tool with the purpose of refining the solution provided by the CHAs. Fig. 3 illustrates the hybrid tool that was developed to solve the STEP problem. It includes the two mentioned CHA algorithms to promote a reduction of the search space and then PSO is used over this reduced search space to identify the most adequate expansion plan.

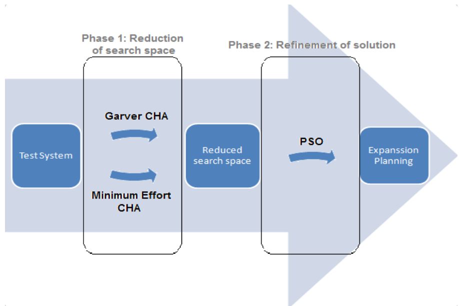

Figure 3. Flow of the tools used in the developed approach.

V. RESULTS

This section presents the results obtained using the hybrid proposed tool applied to the Garver 6-bus and to the Southern Brazilian equivalent 46-bus networks. For comparison purposes we are also presenting the results that are obtained by just using the classical PSO algorithm without the previous applying the described CHA's techniques. It is also important to indicate that all test were conducted admitting that the generation could be rescheduled and also without this possibility. Not considering rescheduling means that the generation pattern is pre-determined in order to supply the demand while if rescheduling is considering then generation outputs can be change in order to minimize the overall cost. It is then clear that admitting rescheduling gives the problem extra flexibility and so the expansion cost will be smaller when compared with the one without rescheduling. The algorithm was implemented in MATLAB, running on an Intel i5, 2.53GHz, 4GB RAM, hardware platform. The tests were performed considering power generation with and without reschedule generation.

A. Garver 6-Bus System

This system consists of 6 bars, 6 existing circuits at the base topology, 15 candidate circuits for expansion admitting that it is allowed to build up to 4 circuits in each path, and forecasted demand for the planning horizon of 760 MW. Therefore, the size of the search space of the STEP problem is 5^{15}. The system data and topology can be obtained in [1].

A.1. Case 1 – With Rescheduled Generation

To simulate the Garver 6-bus system with reschedule generation we considered the following parameters: (i) 1MW tolerance for the total load shedding; (ii) swarm composed of 100 particles; (iii) stopping criterion of 100 iterations or 20 iterations with the same best global result (); (iv) $c_1 = c_2 = 2$ and (v) $\alpha = 100$.

Using these parameters, the proposed tool was applied. In the first phase, *reduction of the search space size,* 3 circuits ($n_{2-6}, n_{3-5}, n_{4-6}$) were selected in just 0.4 seconds, which has reduced the search space from 5^{15} to 5^3, i.e, a reduction larger than 99%. In the second phase, *refinement of the solution*, the PSO was applied over the reduced search space and the best known solution was obtained with additions in $n_{3-5} = 1$ and $n_{4-6} = 3$. The cost of this expansion plan is US$ 110. The process converged to the solution in 23 iterations solving 2300 optimization problems (associated problems to the STEP problem) in 30.3 seconds, which results in a total computation time of approximately 31 seconds. Fig. 4 shows the evolution of the expansion cost of the gbest particle, that is the cost of the particle that in each iteration of the PSO algorithm has the lowest cost.

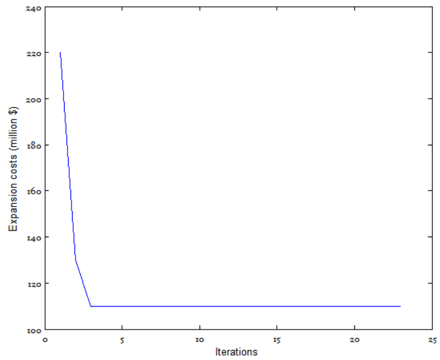

Figure 4. Evolution of the expansion cost along the PSO algorithm – Garver 6-bus system – Case 1.

In order to evaluate the performance of the proposed hybrid tool, we used the PSO algorithm without considering the CHA's techniques. In this case, considering the same parameters indicated previously, the PSO provided the same best solution after running 26 iterations solving 2600 optimization problems in approximately 55 seconds. Table 1 shows the main results that were obtained in these tests.

TABLE I. GARVER 6-BUS SYSTEM WITH RESCHEDULE GENERATION

Tool	Results obtained			
	Reduction of the search space in phase 1	***Expansion costs (US$)***	***Iterations***	***Time (s)***
CHA+PSO	99%	110	23	31
PSO	---	110	26	55

A.2. Case 2 – Without Rescheduled Generation

In this simulation we considered the same parameters as in Case 1. The proposed tool was applied and in phase 1 it has selected 4 circuits ($n_{2-6}, n_{3-5}, n_{4-6}, n_{5-6}$) in just 0.7 seconds, which has reduced the search space from 5^{15} to 5^4, i.e, again a reduction larger than 99%. Then, the PSO was applied in this reduced search space and one of the best known solution was obtained corresponding to additions in $n_{2-6} = 3$, $n_{3-5} = 1$ and $n_{4-6} = 3$, with an expansion cost of US$ 200. The process converged to the solution in 31 iterations solving 3100 optimization problems in 51 seconds, therefore resulting in a total computation time of approximately 52 seconds. Fig. 5 shows the evolution of the cost that was obtained.

Once again, the classical PSO was also applied considering the same previous parameters. In this case the same best solution was obtained with the difference that the process converged to the solution in 48 iterations solving 4800 optimization problems in approximately 215 seconds. The Table 2 shows the main results obtained for the Garver 6-Bus System without reschedule generation.

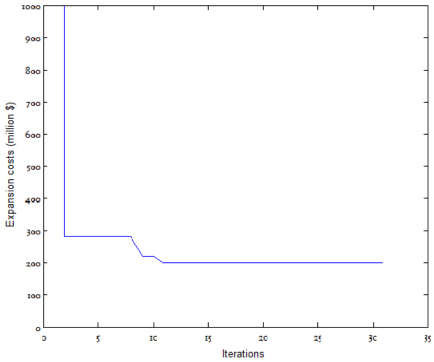

Figure 5. Evolution of the expansion cost along the PSO algorithm – Garver 6-bus system – Case 2.

TABLE II. GARVER 6-BUS WITHOUT RESCHEDULE GENERATION.

Tool	Results obtained			
	Reduction of the search space in phase 1	*Expansion costs (US$)*	*Iterations*	*Time (s)*
CHA+PSO	99%	200	31	51
PSO	---	200	48	215

B. Southern Brazilian Equivalent 46-Bus System

This is an equivalent system and of the southern part of the Brazilian interconnected system. It consists of 46 buses and 79 candidate paths for expansion and we admitted that it is allowed to build up to 2 circuits in each path. The total demand for this system is 6880 MW. The size of the search space of this system is 3^{79}. The system data and topology can be obtained from [12].

B.1. Case 1 – With Rescheduled Generation

In this simulation we considered the following parameters: (i) 1 MW tolerance for the total load shedding; (ii) swarm composed by 100 particles; (iii) stopping criterion of 100 iterations or 20 iterations with the same best global result (gbest); (iv) $c_1 = c_2 = 2$ and (v) $\alpha = 100$.

Using these parameters, the proposed tool was applied and in the first phase 22 circuits were selected $(n_{2-3}, n_{3-46}, n_{5-6}, n_{6-46}, n_{12-14}, n_{13-20}, n_{16-32}, n_{17-19}, n_{19-21}, n_{19-25}, n_{20-21}, n_{20-23}, n_{21-25}, n_{24-25}, n_{28-31}, n_{28-43}, n_{31-32}, n_{31-41}, n_{32-43}, n_{40-41}, n_{40-45}, n_{42-43})$ in 4.88 seconds. This provided a reduction of the search space from 3^{79} to 3^{22}, i.e, a reduction larger than 99%. Thus, in the second phase the PSO was applied over the reduced search space and the best known solution for Southern Brazilian equivalent system with reschedule generation was obtained, with the following additions $\eta_{5-6} = 2$, $\eta_{6-46} = 1$, $\eta_{13-20} = 1$, $\eta_{10-21} = 2$, $\eta_{20-23} = 1$ and $\eta_{42-43} = 1$. The cost of this expansion plan is US$ 70,289.000. The process converged to this solution in 45 iterations solving 4500 optimization problems in 984 seconds, which results in a total computation time of approximately 989 seconds. Fig 6 shows the evolution of expansion cost along the PSO algorithm.

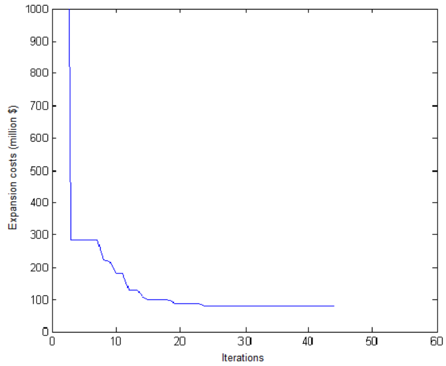

Figure 6. Evolution of the expansion cost along the PSO algorithm – Southern Brazilian – Case 1.

Once again, in order to evaluate the performance of the proposed hybrid tool, the PSO was applied alone considering the same previous parameters. The same solution was obtained with an expansion costs US$ 70,289.000. In this case, the process converged to this solution in 59 iterations solving 5900 optimization problems in 1392 seconds, that is, with more computational effort than the proposed tool. Table III shows the main results obtained in these two simulations.

TABLE III. SOUTHERN BRAZILIAN WITH RESCHEDULE GENERATION WITH RESCHEDULED GENERATION.

Tool	Results obtained			
	Reduction of the search space in phase 1	*Expansion costs (US$)*	*Iterations*	*Time (s)*
CHA+PSO	99%	70,289.000	45	989
PSO	---	70,289.000	59	1392

B.2. Case 2 – Without Rescheduled Generation

The Southern Brazil Equivalent system without reschedule generation was also simulated using the same parameters that were indicated for the previous case. In this simulation we admitted that up to 3 circuits can be built in each candidate path. Therefore, the size of the search space of this system is 4^{79}. The proposed hybrid tool was applied and in phase 1 has selected 27 circuits in 16 seconds, namely: $n_{2-3}, n_{3-46}, n_{5-6}, n_{6-46}, n_{9-10}, n_{10-46}, n_{12-14}, n_{16-28}, n_{16-32}, n_{17-19}, n_{19-21}, n_{19-25}, n_{20-21}, n_{21-25}, n_{24-25}, n_{25-32}, n_{26-29}, n_{28-30}, n_{28-31}, n_{28-43}, n_{29-30}, n_{31-32}, n_{31-41}, n_{32-43}, n_{40-41}, n_{40-45}, n_{42-43}$. This reduced the search space from 4^{79} to 4^{27}, i.e, again a reduction larger than 99%. As in the previous cases, the PSO was then applied over this reduced search space and the best known solution was obtained corresponding to additions in $\eta_{5-6} = 2$, $\eta_{6-46} = 1$, $\eta_{19-25} = 1$, $\eta_{20-21} = 1$, $\eta_{24-25} = 2$,

$\eta_{26-29}=3$, $\eta_{28-30}=1$, $\eta_{29-30}=2$, $\eta_{31-32}=1$ and $\eta_{42-43}=2$ with an expansion cost of US$ 154,420.000. The process converged to the solution in 64 iterations solving 6400 optimization problems in 1540 seconds, therefore, resulting in a total computation time of approximately 1556 seconds. Fig. 7 shows the evolution of the expansion cost.

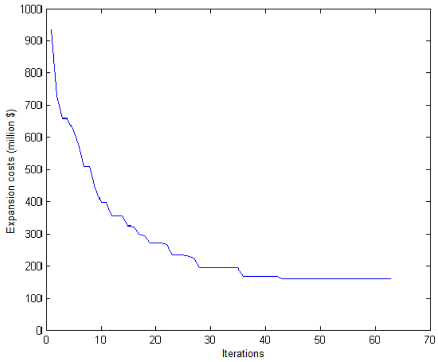

Figure 7. Evolution of the expansion cost along the PSO algorithm – Southern Brazilian – Case 2.

Finally, the PSO alone was applied considering the same previous parameters and a new solution was obtained with the addition of 16 circuits: $\eta_{5-6}=2$, $\eta_{6-46}=1$, $\eta_{16-28}=1$, $\eta_{18-20}=1$, $\eta_{20-21}=2$, $\eta_{20-23}=2$, $\eta_{31-32}=1$, $\eta_{32-41}=1$, $\eta_{40-41}=3$ and $\eta_{40-42}=2$. The cost of this expansion plan is US$ 180,430.000. The process converged to this solution in 81 iterations solving 8100 optimization problems in 1890 seconds. Finally, Table IV shows the main results obtained for the Southern Brazil Equivalent system without reschedule generation.

TABLE IV. SOUTHERN BRAZILIAN WITHOUT RESCHEDULE GENERATION

Tool	Results obtained			
	Reduction of the search space in phase 1	***Expansion costs (US$)***	***Iterations***	***Time (s)***
CHA+PSO	99%	154,420.000	64	1556
PSO	---	180,430.000	81	1890

VI. CONCLUSIONS

In this paper describes an hybrid tool to solve the STEP problem. This tool is structured in two phases as follows. The first one is performed through two heuristics, Garver CHA and Minimum Effort CHA in order to reduce the set of candidate routes, i.e, to reduce efficiently the search space of the STEP problem. In the second phase we used PSO to go over the selected routes from first phase in order to refine the solution resulting in an expansion plan. This tool was applied in two test systems, Garver 6-bus and Southern Brazil 46-bus. The Garver system, although being a small system, is widely used in the literature for comparison purposes. The second tested network is based on the Southern Brazilian transmission system and given its size it allows taking more meaningful conclusions on the performance of the developed approach. In all tested situations, it was possible to reduce the search space more than 99% after completing the first phase. At the end of the second phase, the final expansion plan provided by the combined use of the two CHA's and the PSO is the same or is better than the one that is obtained by just using the PSO as indicated in Tables I to IV.

These results confirm that the hybridization between CHAs and PSO used to reduce the search space and to identify the final solution is a powerful tool because it has the ability to find adequate expansion plans in an efficient way when compared with other techniques. Therefore, future work will be developed in this area namely to continue testing other hybridization combinations and also to pass from a single period static analysis to a multiperiod formulation.

ACKNOWLEDGMENT

The first author thanks CAPES Foundation, Ministry of Education of Brazil, for financing this research.

The research leading to this work is being carried out as part of the evolvDSO project (Development of methodologies and tools for new and evolving DSO roles for efficient DRES integration in distribution networks) - www.evolvdso.eu. This project is funded by the European Commission under the 7th framework program (FP7) under grant agreement 608 732.

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B.0.2 Multiyear and multi-criteria ac transmission expansion planning model considering reliability and investment costs. (IEEE European Energy Market, 2016)

Multiyear and Multi-Criteria AC Transmission Expansion Planning Model Considering Reliability and Investment Costs

Phillipe Vilaça Gomes, João Pedro Silva and João Tomé Saraiva
INESC TEC and FEUP/DEEC
Dept. Eng. Eletrotécnica e de Computadores da Faculdade de Engenharia da Universidade do Porto - Portugal
phillipe.gomes@fe.up.pt, joaopedrosilva91@gmail.com, jsaraiva@fe.up.pt

***Abstract* — One of the major concerns in Power Systems is surely related with their reliability. Long-term expansion planning studies traditionally use the well-known deterministic "N-1" contingency criterion. However, this criterion is applied based on worst-case analyses and the obtained plan may originate over-investments. Differently, probabilistic reliability approaches can incorporate different type of uncertainties that affect power systems. In this work, a long term multi-criteria AC Transmission Expansion Planning model was developed considering two objectives - the probabilistic reliability index Expected Energy Not Supplied (EENS) and the investment cost. The Pareto-Front associated with these two objectives was obtained using Genetic Algorithms and the final solution was selected using a fuzzy decision making function. This approach was applied to the IEEE 24 Bus Test System and the results ensure its robustness and efficiency.**

***Index Terms* — Multi-Criteria and Multi-Year Transmission Expansion Planning, Pareto-Front, Fuzzy Decision Making, EENS, AC-Optimal Power Flow.**

I. INTRODUCTION

The main objective of the Transmission Expansion Planning (TEP) Problem is to define where, when and how a transmission system should be modified in order to adequately meet the future demand. This exercise can be conducted in order to consider several objective functions as minimizing the investment and operation costs, increasing the system reliability, minimizing the greenhouse gas emissions, increasing the flexibility of system operation while reducing the network charges, providing a better voltage profile, etc. Besides, the TEP problem can be modelled considering static or a dynamic (multiyear) approaches. In the first option, the study is performed considering each period at a time in a way that the equipments (transmission lines, cables or transformers) selected to expand the system in one period are considered on the basis topology for the subsequent ones. On the other hand, the multiyear approaches take the horizon in a holistic way and the problem is solved in a single run for all periods. It is noteworthy that the multiyear TEP preserves the holistic planning view and this is essential to obtain good quality long-term expansion plans. The experience of the authors also indicates that solving the TEP problem using a static year by year approach originates a global solution with a cost that is not inferior to the cost associated to the multiyear approach. This result is just the application of the well-known rule indicating that the aggregation of partial optima is not superior to the optimum coming from a global analysis.

One of the major concerns in Power Systems is surely related with their reliability, which in turn can be studied using deterministic or probabilistic approaches. Traditionally, TEP is conducted using the well-known deterministic "N-1" criterion. This criterion is applied based on worst-case analyses (draw from single contingency). However, this approach does not define consistently the true risk of the system, since it does not take into account how systems operates, how components fail and the existence of different load levels. In addition, the "N-1" criterion usually originates over-investments [1]. Differently, probabilistic approaches allow incorporating uncertainties associated to the non-ideal behavior of power system components. Meantime, the probabilistic approaches require pre-defining the reliability indices to be used, which in turn, may introduce some subjectivity in the analysis. As stated in [2], these aspects explain the dichotomy between deterministic and probabilistic approaches regarding the TEP problem.

In this paper a Multi-Criteria and Multi-Year Transmission Expansion Planning was developed considering two objectives - the investment cost and the probabilistic reliability index Expected Energy Not-Supplied (EENS). The developed approach uses a Non-Dominative CHA-Climbing Genetic Algorithm (NDCCGA) to build the Pareto-Front of the optimization problem and using this front it is then used a Fuzzy Decision Making Function (FDMF) to select the final expansion plan.

Regarding the structure of the paper, following this Introduction, Section II presents the AC model for the TEP problem and Section III provides a brief analysis of Reliability studies in power systems as well as the main steps of the chronological Monte Carlo Simulation to estimate the EENS index. Section IV details the NDCCGA tool and its main blocks, Section V presents a brief description of Fuzzy

The research leading to this work is funded by the CAPES under BEX number 13207-13-0.

Decision Making and Section VI provides the results obtained in the simulations. Finally Section VII includes some comments and the conclusions about this work.

II. TEP Mathematical Formulation

The most adequate model to deal with TEP problems is the AC power flow (AC-OPF) operation model because it considers the reactive power, the losses and the bus voltage limits. However, this model is more demanding from a computational point of view than DC based models, thus requiring the use of very efficient optimization techniques to solve AC-OPF problems.

The AC-OPF used in this paper is formulated by (1) to (9).

$$\text{Min } C_{OP} = \sum \alpha_{i1}.P_i^2 + \alpha_{i2}.P_i + \alpha_{i3} \quad (1)$$

subject to

$$P(V,\theta,n) - P_G + P_D = 0 \quad (2)$$

$$Q(V,\theta,n) - Q_G + Q_D = 0 \quad (3)$$

$$P_{G\min} \le P_G \le P_{G\max} \quad (4)$$

$$Q_{G\min} \le Q_G \le Q_{G\max} \quad (5)$$

$$V_{\min} \le V \le V_{\max} \quad (6)$$

$$(N + \overset{o}{N})S^{from} \le (N + \overset{o}{N})S_{\max} \quad (7)$$

$$(N + \overset{o}{N})S^{to} \le (N + \overset{o}{N})S_{\max} \quad (8)$$

$$0 \le n \le n_{\max} \quad (9)$$

In this formulation $P(V,\theta,n)$ and $Q(V,\theta,n)$ are calculated by (10) and (11), and the bus conductance G and susceptance B are given by (12) and (13).

$$P(V,\theta,n) = V_i \sum V_j [G_{ij}(n).\cos\theta_{ij} + B_{ij}(n).\sin\theta_{ij}] \quad (10)$$

$$Q(V,\theta,n) = V_i \sum V_j [G_{ij}(n).\sin\theta_{ij} - B_{ij}(n).\cos\theta_{ij}] \quad (11)$$

$$G = \begin{Bmatrix} G_{ij}(n) = -(n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \\ G_{ii}(n) = \sum_{j \in \Omega_i} (n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \end{Bmatrix} \quad (12)$$

$$B = \begin{Bmatrix} B_{ij}(n) = -(n_{ij}.b_{ij} + \overset{o}{n}_{ij}.\overset{o}{b}_{ij}) \\ B_{ii}(n) = b_{ij}^{sh} + \sum_{j \in \Omega_i} [n_{ij}(b_{ij} + b_{ij}^{sh}) + \overset{o}{n}_{ij}(\overset{o}{b}_{ij} + \overset{o}{b}{}_{ij}^{sh})] \end{Bmatrix} \quad (13)$$

The apparent flows S_{ij}^{from} and S_{ij}^{to} in branch ij are calculated by (14) and (15) where P_{ij}^{from}, Q_{ij}^{from}, P_{ij}^{to} and Q_{ij}^{to} are given by (16) to (19).

$$S_{ij}^{from} = \sqrt{(P_{ij}^{from})^2 + (Q_{ij}^{from})^2} \quad (14)$$

$$S_{ij}^{to} = \sqrt{(P_{ij}^{to})^2 + (Q_{ij}^{to})^2} \quad (15)$$

$$P_{ij}^{from} = V_i^2.g_{ij} - V_i.V_j(g_{ij}.\cos\theta_{ij} + b_{ij}.\sin\theta_{ij}) \quad (16)$$

$$Q_{ij}^{from} = -V_i^2.(b_{ij}^{sh} + b_{ij}) - V_i.V_j(g_{ij}.\sin\theta_{ij} - b_{ij}.\cos\theta_{ij}) \quad (17)$$

$$P_{ij}^{to} = V_j^2.g_{ij} - V_i.V_j(g_{ij}.\cos\theta_{ij} - b_{ij}.\sin\theta_{ij}) \quad (18)$$

$$Q_{ij}^{to} = -V_j^2.(b_{ij}^{sh} + b_{ij}) + V_i.V_j(g_{ij}.\sin\theta_{ij} + b_{ij}.\cos\theta_{ij}) \quad (19)$$

In this formulation, the objective function (1) corresponds to the operation cost of a thermal system where α_{i1}, α_{i2} and α_{i3} are coefficients of the quadratic generator cost functions of each generation unit *i* dispatching a real power P_i. P_G is the real power generation, Q_G is the reactive power generation, P_D is the real power demand, Q_D is the reactive power demand, V is the voltage magnitude, S_{ij}^{from} and S_{ij}^{to} are the branch apparent flows in terminals, and g_{ij} and b_{ij} are the conductance and the susceptance of branch i-j.

III. Reliability in Power systems

A. Overview on power system reliability methods

In the assessment of power systems reliability, there are two different approaches that allow evaluating the adequacy of a power system and that can be used in TEP models: deterministic and probabilistic approaches. Deterministic criteria are based on a pre-specified rule that is defined considering the experience obtained through the analyses of other power systems. In TEP, the N-1 deterministic criterion to model likely failures is often taken in account. However, this approach does not consider the stochastic behaviour of power systems. This means that in order to consider uncertainties related to power systems such as the possible failure of system components, the weather conditions or the demand growth, a stochastic model should be followed. Markov processes are the well-known reference that allow including different system states. Figure 1 shows a typical two-state Markov model in which the failure and repair rates are modelled by exponential distributions. In other words, these distributions model the duration of the system events.

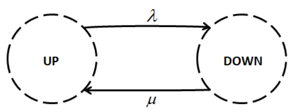

Figure 1: Markov model composed by two states, where λ is the failure rate and μ is the repair rate.

Regarding the probabilistic approaches, there are two main families of methods that should be mentioned: the analytical and the simulation ones. The calculation of system reliability indices is the main goal of both approaches. However the application of analytical methods to complex power systems is not adequate due to the number of simplifications and assumptions that usually need to be accepted. The simulation processes are commonly known as Monte Carlo Simulations (MCS). MCS uses a random sampling of states in order to estimate the reliability indices. There are two different types of MCS: the chronological and the non-chronological. Since the developed TEP approach uses the EENS to characterize the system reliability, it is important to keep track of the sequence of states determining the life of the system together with their duration. Therefore, in this paper, the chronological MCS will be used to estimate the EENS index as it will be detailed in the next Section.

B. Chronological Monte Carlo Simulation to estimate the Expected Energy Not Supplied, EENS

As mentioned before, the developed multiyear TEP problem includes the EENS to measure the reliability of the system under analysis. If just a non-chronological MCS was used, each system state was characterized by the on or off state of each component, an AC OPF could be run considering the on components and the associated Power Not Supplied could then be obtained. However, there would be no indication about the duration of each state in the sense that the operation-failure cycle of each component was not considered. In order to get more insight on system operation and to pass from PNS to ENS it is necessary to sample operation and repair times of the components thus justifying the use of a chronological Monte Carlo to estimate the EENS. The chronological or sequential MCS approach requires using the failure density function to model the operation and repair times of each component usually modeled by an exponential distribution [3]. The main blocks of the chronological MCS to evaluate reliability indices are presented below.

Procedure Chronological MCS

Initialize system data: MTTF, MTTR, pre-specified β

Do

Initialize the system state: through the selected probability distribution, sample the operating time of each system component.

Repeat

> *Pick the lowest sampled time. Let **F** be the associated component.*
>
> *Evaluate the system state. According to this system state, calculate the power not supplied and then the energy not supplied multiplying the power not supplied by the duration of the current system state.*
>
> *Update the accumulators of the reliability indices.*
>
> *Depending on the previous state of component F, sample a new operating or repair time.*
>
> *Update the state and the lifetime of F.*
>
> *Evaluate the system lifetime. For each year of simulation, the reliability indices must be updated as well as the coefficient of variation β.*

Until coefficient of variation β or the maximum number of years is reached.

End Chronological MCS

The previous sequential MCS blocks show that for each system component an operation-repair life cycle is developed. Using this cycle, the energy not supplied can be calculated for each system state and consequently it is possible to obtain an estimate for EENS. This index reflects states in which the load is not fully supplied because it exceeds the available generation capacity and/or because there is insufficient branch transmission capacity.

IV. NON-DOMINATIVE HILL-CLIMBING GENETIC ALGORITHM, NDCCGA

The main blocks of the NDCCGA are similar to the ones of a genetic algorithm applied to solve the TEP problem. Additionally, it includes an improvement population block, a Tabu list to control the diversity of the population and a genetic similarity control to ensure the elite diversity through the generations. The main NDCCGA blocks are presented below and detailed in the next sections.

Procedure NDCCGA

Set the list of projects having *nproj* elements.

Initialize a random population with *ps* individuals.

Repeat

> *Reproduction*
>
> *Mutation*
>
> *Improvement*
>
> *Evaluation*
>
> *Selection*
>
> *Similarity Control*
>
> *Stop Test*

Until test is positive

End NDCCGA

A. Possible projects – The Search Space Reduction

The planner should specify a list of possible projects defined in terms of the extreme nodes, type (overhead line or transformer), transmission capacity and investment cost. The TEP algorithm should then select some of the elements in this list to be integrated in the expansion plan and locate them in one of the years of the horizon. The current approach restricts these projects to corridors already used in the base topology although it can be adapted to allow using new corridors. On the other hand, using a large number of branches can turn the computational effort to solve the TEP problem prohibitive. Therefore, the search space was reduced using a Constructive Heuristic Algorithm (CHA) detailed in [4].

B. Particle Codification

Each individual corresponds to an expansion solution plan and it is encoded by a vector that includes as many genes as the number of equipments in the reduced list coming from the CHA mentioned in IV.A. Each gene contains an integer number that represents the period of the planning horizon in which this equipment will be inserted into the network.

C. Creating the Initial Population

The initial population is randomly created with the aid of a Tabu List which ensures the diversity of this population.

D. Reproduction

In the reproduction block pairs of individuals randomly chosen are used to create an offspring. Differently from usual crossover strategies in which just one position in each individual is sampled, in this case we sample two positions. Starting with the first individual we sample another one to form a pair, then two positions are sampled in these two individuals and one offspring is created. This procedure is repeated until all individuals undergo reproduction thus creating a new population with the same size as the initial one.

E. Mutation

The mutation only affects a small percentage of the offsprings and it aims at increasing the diversity of a particular individual. Once an individual is selected, a particular gene is randomly sampled and then its associated integer number is modified. If this integer number is increased, than this means postponing the construction of the associated equipment.

F. Improvement Block

The improvement block is based on the individual's characteristics, that is, if an individual has an unacceptable value for PNS for a particular year, it is improved inserting new equipments selected using a CHA. On the other hand, if this individual displays a PNS value below a threshold, it is modified by eliminating equipments using the Hill Climbing Method. According to this method, an equipment is removed and the new individual is evaluated again. If the resulting PNS value continues below the threshold this change is confirmed. If not, that equipment is included back in the individual. These algorithms are detailed in [5] and they are used as a way to accelerate the convergence of the genetic algorithm reducing the investment cost or the EENS index of some solutions.

G. Evaluation

In the evaluation block the values of investment cost and EENS are calculated. In a first moment, the PNS is obtained by running the AC-OPF using (1) to (9). If this value is greater than zero the fitness function (20) is calculated and the EENS is set at β_2 (high value). If the PNS is zero the EENS is obtained as described in Section III. In (20) p is the period in study, np is the total number of periods, r is the return rate and β_1 is the penalty factor for PNS.

$$fitness = \sum_{p=1}^{np} \frac{C_{inv,p}}{(1+r)^p} + \beta_1 . PNS \qquad (20)$$

H. Selection

The selection is performed in two steps as follows. In the first place, the non-dominated solutions are selected, regarding the objectives investment costs and EENS, and included in the new population. In the second step it is used a tournament selection with the remaining solutions to complete the population until its original size is reached.

I. Genetic Similarity Control

The non-dominated solutions coming from the first step of the Selection process are subjected to a similarity control to increase the diversity of the new population. This control uses the concept of parent circle of radius r as illustrated in Figure 2. For each non-dominated solution a parental circle is used around it. If another solution is located inside this circle, then the solution having the highest investment cost is discarded.

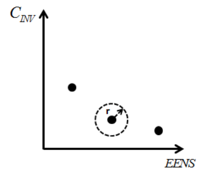

Figure 2: Illustration of the concept of parental circle.

J. Stopping Criterion

The stopping criterion is based on the set of non-dominant solutions. If this set remains unchanged for a pre specified number of iterations the iterative process ends.

V. Fuzzy Decision Making

Once the Pareto-front is built, the decision maker has a number of solutions characterized by the corresponding investment cost and EENS. In order to help the decision maker to select the final solution we used a fuzzy decision making function according to which the membership function μ_i measures the adequacy of each solution k in the Pareto front regarding a specific objective function for each i ($f_1 = C_{INV}$ and $f_2 = EENS$). Figure 3 illustrates the concept associated with this approach. For each objective function i, f_i , the decision maker specifies a minimum and a maximum level, so that if a solution k has a value for f_i less than the minimum, then a 1,0 membership degree is assigned. If the value of f_i is between the minimum and the maximum then a membership degree decreasing from 1,0 to 0,0 is associated indicating that solution k is less compatible with the concept of being a good quality solution in the sense of minimizing the objective f_i. Finally, if the value of f_i is larger than the maximum level then the solution k has bad quality and it is eliminated. Once having the membership degrees regarding the two objectives for a solution k, then the minimum of the two is taken and this value is used to characterize solution k. Among all the solutions in the Pareto Front, it will be selected the one having the maximum of the minimum values of the corresponding objectives as it is translated by (20).

$$Decision = \max_k (\min(\mu(C_{INV_k}), \mu(EENS_k))) \qquad (21)$$

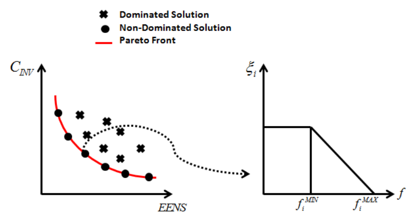

Figure 3: Fuzzy Mechanism for Best Comparison

VI. Tests and Results

The Non-Dominative CHA-Climbing Genetic Algorithm described in Section IV was applied on the modified IEEE 24 Bus Reliability Test System. The system used in the tests has some differences regarding the original system proposed in [6] and the system details can be found in [3] and [4].

The tests were performed considering the multiyear TEP model with 3 periods and using a load increase of 5% per period. The original list of equipments includes 38 lines and transformers and in the first place the CHA was applied to select a sub-list of candidate equipments considering a static TEP problem for each period. After solving 23 AC-OPFs, using the MATPOWER tool described in [7], running in MATLAB with an Intel i7, 3.4GHz, 8 GB RAM, the CHA selected 10 branches for possible reinforcement from the initial 38 equipments leading to a reduction of 99% in the search space. The equipments that result from search space reduction step are the ones connecting buses 1-5, 3-24, 6-10, 7-8, 11-13, 13-23, 14-16, 15-24, 16-17, 17-18, in which it is permitted build up to 3 circuits for each path.

The simulations were performed in MATLAB with an Intel i7, 3.4GHz, 8 GB RAM. The NDCCGA used 50 individuals in the population and the parent circle radius was set at 10^4 . The parameters for the CHA and the Hill Climbing methods are the same as used in [5]. The simulation involved solving about 1200000 AC-OPFs in about 100 hours. Figure 4 shows the solutions obtained, in which the vertical axis corresponds to the present value of the investment cost, that is, the sum of the investment cost in the three periods brought back to the departing period using a return rate of 5% per year. The horizontal represents the EENS for the three years.

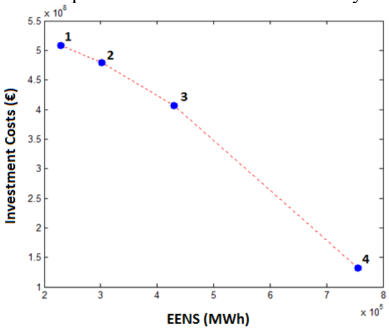

Figure 4: Pareto-Front associated with the investment cost and EENS.

The shape of this front deserves a comment because it behaves differently regarding the theoretical illustration in Figure 3. The TEP problem has a discrete nature so that including a new equipment in the expansion plan or changing the set of equipments to pass, for instance, from solution 4 to solution 3 leads to discrete jump in the investment cost. Apart from that, the evaluation of EENS requires solving non-linear AC problems. Together, these two issues determine that a convex shape has the one in Figure 3 is not always obtained in the case of the TEP problem.

TABLE I. BEST SOLUTION IDENTIFIED BY THE FUZZY DECISION MAKING

Period	New equipment	Invest. Cost (€)	EENS (MWh)
1	1-5, 6-10, 7-8, 11-13	120.10^6	$46,2.10^3$
2	7-8, 11-13, (2) 14-16, 15-24	262.10^6	$205,43.10^3$
3	1-5, 3-24, 16-17	108.10^6	$178,87.10^3$

After building the Pareto-Front, it was used the Fuzzy Decision Making described in Section V. For each Pareto Front solution k, it was calculated the membership function given by (20). The final solution corresponds to solution 3 in Figure 4 and detailed in Table I.

VII. CONCLUSIONS

This paper presents a dynamic approach of the Transmission Expansion Planning problem using a multi-criteria analysis that considers the total investment cost and the Expected Energy Not Supplied as the objectives. The problem was solved using the Non-Dominative CHA-Climbing Genetic Algorithm tool developed by Vilaça and Saraiva in [5]. A Fuzzy decision making process is then used to select the final expansion plan among the solutions in the Pareto Front. The EENS index was estimated using a Chronological Monte Carlo Simulation.

The NDCCGA was applied to the modified IEEE 24-Bus Reliability Test System and showed excellent performance to deal with the large computational effort required to estimate the EENS and to solve the AC-OPFs. The tool provided a set of 4 final solutions with different values of investment cost and EENS. On the other hand, the adoption of multi-objective approaches is very relevant as a way to turn the TEP problem more realistic. It also offers a trade-off analysis between objectives instead of other techniques that, for instance, require transforming all objectives except one in constraints or building a value function that aggregates all the individual objectives using weights specified by the user.

As future work, the developed toll can be parallelized to take advantage of multi-core machines.

ACKNOWLEDGMENT

P. Vilaça acknowledges the financial support from CAPES Scholarship under Bex 13207-13-0.

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B.0.3 Evaluation of the performance of space reduction technique using ac and dc models in transmission expansion problems. (IEEE European Energy Market, 2016)

Evaluation of the Performance of Space Reduction Technique Using AC and DC Models in Transmission Expansion Problems

Phillipe Vilaça Gomes and João Tomé Saraiva
INESC TEC and FEUP/DEEC
Dept. Eng. Eletrotécnica e de Computadores da Faculdade de Engenharia da Universidade do Porto - Portugal
phillipe.gomes@fe.up.pt, jsaraiva@fe.up.pt

***Abstract* — Transmission Expansion Planning (TEP) is an optimization problem that has a non-convex and combinatorial search space so that several solution algorithms may converge to local optima. Therefore, many works have been proposed to solve the TEP problem considering its relaxation or reducing its search space. In any case, relaxation and reduction approaches should not compromise the quality of the final solution. This paper aims at analyzing the performance of a search space technique using a Constructive Heuristic Algorithm (CHA) admitting that the TEP problem is then solved using a Discreet Evolutionary Particle Swarm Optimization (DEPSO). On one hand the reduction quality is performed by analyzing whether the optimal expansion routes are included in the CHA constrained set and, on the other hand, the relaxation quality of the DC model is analyzed by checking if the optimal solution obtained with it violates any constraint using the AC model. The simulations were performed using three different test systems. The results suggest that the proposed CHA provides very good results in reducing the TEP search space and that the adoption of the DC model originates several violations if the full AC model is used to model the operation of the power system.**

***Index Terms* —Multi-Year Transmission Expansion Planning, Constructive Heuristic Algorithm, Discrete Evolutionary Particle Swarm Optimization.**

I. INTRODUCTION

The increasing demand for electricity requires planning the expansion of power systems in a careful way so that they can meet the future demand in a secure and reliable way. The changes on an existing power system usually correspond to build new generating facilities if possible close to demand centers or connecting sub-regions through transmission lines. However, the first option is frequently not economically feasible or even possible. Apart from that, the connection of sub-systems can enable the optimal dispatch of power plants. Therefore, the TEP problem aims at defining when, where and what equipment (transmission lines, cables or transformers) should be built in order to optimize a predetermined objective (minimizing or maximizing some function) along an extended horizon and meeting a number of constraints. The objectives to be optimized are usually:

- Minimization of the investment and operation costs;
- Increase of the system reliability;
- Minimization of the greenhouse gas emissions;
- Obtaining an improved voltage profile.

The TEP exercise can be conducted considering static or dynamic (multiyear) approaches. In the static TEP models the equipment selected to include in the network in one period are considered in the basis topology for the subsequent one which means that using a static approach for an extended horizon implies solving the TEP problem as many times as the time steps in that horizon. In multiyear approaches the problem is solved in a single run considering all periods in the same formulation. This means taking the horizon in a holistic way and thus turning it possible to obtain better quality long-term expansion plans.

In this paper a TEP multiyear approach was developed in order to minimize the system total cost. This cost reflects the investment and the operational cost, namely associated with Power Not Supplied (PNS), which is related to a penalty term in the objective function of the problem. The developed approach was applied to 3 different test systems considering that generation can be rescheduled. The main objectives of this paper are highlighted below:

- Evaluate the quality of the solution if a reduction search space technique using a CHA algorithm is used together with DC and AC Optimal Power Flow (OPF) models. This means checking whether the CHA is able to identify the main expansion routes without eliminating routes that are part of the final solution;
- Evaluate the quality of the expansion obtained using the DC-OPF model. This means checking if the expansion plan violates any operation constraint modeled using the AC power flow model.

Regarding the structure of the paper, after this Introduction, Section II presents the TEP mathematical model, Sections III and IV provide a brief description of the CHA and DEPSO

The research leading to this work is funded by the CAPES under BEX number 13207-13-0.

techniques, Section V presents the simulation results and Section VI outlines the main conclusions of this work.

II. TEP MATHEMATICAL FORMULATIONS

A. General TEP formulation

The AC-OPF is the most adequate model to deal with TEP problems. However, the TEP problem is a challenging Mixed Integer Non-Convex Non-Linear Program (MINLP) and so several approaches can be used to turn it more tractable as the use of a DC based dispatch model instead of a full AC dispatch model. Following [1], the general formulation of the TEP problem is given by (1-4).

$$\text{Minimize } Z = \sum_{p=1}^{np} \frac{C_p^{inv} + \beta.PNS_p}{(1+r)^p} \quad (1)$$

Subject to:
Physical constraints; (2)
Financial constraints; (3)
Quality of service constraints. (4)

Physical constraints are associated to the generator and branch capacity limits, financial constraints refer to the maximum amount that is available to be invested in a certain period and the quality of service constraints are for instance related with the maximum value allowed for PNS in normal or contingency regimes.

The objective function (1) is calculated through the np periods using the values of the investment cost C_p^{inv} and the PNS_p penalty cost for each period p brought to the departing period using a return rate r. In each period, the value of PNS is obtained from an optimal dispatch problem using the AC or DC models as detailed in the next Section.

B. AC Model based dispatch model

The AC-OPF is formulated by (5) to (13).

$$\text{Min } C_{OP} = \sum_{g=1}^{ng} C_g(P) \quad (5)$$

subject to

$$P(V,\theta,n) - P_G + P_D = 0 \quad (6)$$

$$Q(V,\theta,n) - Q_G + Q_D = 0 \quad (7)$$

$$P_{G\min} \le P_G \le P_{G\max} \quad (8)$$

$$Q_{G\min} \le Q_G \le Q_{G\max} \quad (9)$$

$$V_{\min} \le V \le V_{\max} \quad (10)$$

$$(N + \overset{o}{N})S^{from} \le (N + \overset{o}{N})S_{\max} \quad (11)$$

$$(N + \overset{o}{N})S^{to} \le (N + \overset{o}{N})S_{\max} \quad (12)$$

$$0 \le n \le n_{\max} \quad (13)$$

In this formulation $P(V,\theta,n)$ and $Q(V,\theta,n)$ are calculated by (14) and (15), and the bus conductance G and susceptance B are given by (16) and (17).

$$P(V,\theta,n) = V_i \sum V_j [G_{ij}(n).\cos\theta_{ij} + B_{ij}(n).\sin\theta_{ij}] \quad (14)$$

$$Q(V,\theta,n) = V_i \sum V_j [G_{ij}(n).\sin\theta_{ij} - B_{ij}(n).\cos\theta_{ij}] \quad (15)$$

$$G = \begin{cases} G_{ij}(n) = -(n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \\ G_{ii}(n) = \sum_{j\in\Omega_i} (n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \end{cases} \quad (16)$$

$$B = \begin{cases} B_{ij}(n) = -(n_{ij}.b_{ij} + \overset{o}{n}_{ij}.\overset{o}{b}_{ij}) \\ B_{ii}(n) = b_{ij}^{sh} + \sum_{j\in\Omega_i} [n_{ij}(b_{ij} + b_{ij}^{sh}) + \overset{o}{n}_{ij}(\overset{o}{b}_{ij} + \overset{o}{b}_{ij}^{sh})] \end{cases} \quad (17)$$

The apparent flows S_{ij}^{from} and S_{ij}^{to} in branch ij are calculated by (18) and (19) where P_{ij}^{from}, Q_{ij}^{from}, P_{ij}^{to} and Q_{ij}^{to} are given by (20) to (23).

$$S_{ij}^{from} = \sqrt{(P_{ij}^{from})^2 + (Q_{ij}^{from})^2} \quad (18)$$

$$S_{ij}^{to} = \sqrt{(P_{ij}^{to})^2 + (Q_{ij}^{to})^2} \quad (19)$$

$$P_{ij}^{from} = V_i^2.g_{ij} - V_i.V_j(g_{ij}.\cos\theta_{ij} + b_{ij}.\sin\theta_{ij}) \quad (20)$$

$$Q_{ij}^{from} = -V_i^2.(b_{ij}^{sh} + b_{ij}) - V_i.V_j(g_{ij}.\sin\theta_{ij} - b_{ij}.\cos\theta_{ij}) \quad (21)$$

$$P_{ij}^{to} = V_j^2.g_{ij} - V_i.V_j(g_{ij}.\cos\theta_{ij} - b_{ij}.\sin\theta_{ij}) \quad (22)$$

$$Q_{ij}^{to} = -V_j^2.(b_{ij}^{sh} + b_{ij}) + V_i.V_j(g_{ij}.\sin\theta_{ij} + b_{ij}.\cos\theta_{ij}) \quad (23)$$

In this formulation, the objective function (5) corresponds to the system operation cost with ng generation units, which in turn is the sum of the dispatch in each unit g.. P_G and Q_G are the real and reactive power generation, P_D and Q_D are the real and reactive power demand, V is the voltage magnitude, S_{ij}^{from} and S_{ij}^{to} are the branch apparent flows in both terminals, and g_{ij} and b_{ij} are the conductance and the susceptance of branch i-j, $\overset{o}{N}$ and N are diagonal matrices containing the equipment in the base topology and the added equipment respectively.

C. DC Model

The DC OPF model is the most popular approximation to the AC OPF model. According to [2], this model admits that the voltage magnitudes are close to 1 pu, branch susceptance are much larger than the corresponding branch conductance and the phase angle difference across each branch is negligible. As a result $\sin(\theta_i - \theta_j) \approx \theta_i - \theta_j$ and $\cos(\theta_i - \theta_j) \approx 1$ and so equation (20) is approximated by (24).

$$P_{ij} = b_{ij}.(\theta_i - \theta_j) \quad (24)$$

III. CONSTRUCTIVE HEURISTIC ALGORITHM TO REDUCE THE SEARCH SPACE

CHAs are tools that use a sensitivity function to iteratively drive the selection of new elements to include in the solution till the final plan is obtained. In general, the output of CHA algorithms include a number of branches larger than the ones in an optimal plan which means that their output can be used as input in a subsequent optimization procedure to obtain the final plan. If CHA's are used like this, that is to reduce the search space, the performance of the subsequent optimization module can be largely improved. More information about the CHA procedures can be accessed in [3]. The following pseudo code briefly details the main steps of the Least Effort CHA.

Procedure CHA

Do

Check if the base topology presents PNS for a determined horizon plan.

Repeat

Solve the Optimal Power Flow model

Check the most congested equipment in the system

Insert an equipment in parallel to this one

Update the system with the new equipment

Until the current topology does not present PNS

End Least Effort CHA

IV. Discrete Evolutionary Particle Swarm Optimization

DEPSO was originally reported in [4] and it provides an adaptation of the Evolutionary Particle Swarm Optimization to solve problems with non-continuous and integer search spaces as the TEP problem. This tool combines the main features of evolutionary computing and swarm intelligence using the main blocks of Genetic Algorithm and Particle Swarm Optimization. Typically, the planner provides a list of N_{proj} equipment that can be used for network expansion. Each particle in DEPSO represents a possible expansion plan and it is encoded by a vector that has N_{proj} positions. Each position is filled with integer values ranging from 0 to Np (number of periods considered in the study) indicating in which period it is included in the network. If 0, then the corresponding equipment is not used in this expansion plan.

The most remarkable features of this tool is the computational effort required to find optimal and sub-optimal solutions. This characteristic is derived from the evolutionary part of the algorithm. On the other hand, the quality of the final solution is closely related to the initial swarm, i.e., the final expansion plan will be better if the particles start their journey from good positions in the search space. This feature is enhanced because DEPSO is a multi-agent population algorithm. These features are very adequate to solve the TEP problem namely if a CHA is used as an initial step because:

- reduction of the search space conducted by the CHA – This can significantly reduce the computational effort and at the same time provides a good initialization for the particles in departing population thereby improving the performance of DEPSO;
- Evaluate the quality of the solution if a DC based dispatch is used – the use of the DC model can also significantly reduce the computational effort associated with the DEPSO.

Therefore, these two features are in line with the main objective of this paper, which is to analyze if these approaches (reduction and approximation) imply any kind of compromise on the goodness of the final expansion plan.

The main DEPSO blocks are presented below.

Procedure DEPSO

Do

Set the list of candidate equipment having N_{proj} elements

Initialize a random population with *ps* particles

Repeat

Replication

Mutation

Recombination

Evaluation

Selection

Stop Test

Until test is positive

End DEPSO

In the replication block, the swarm is replicated *r* times and the elements of these *r* clones are then mutated in order to increase the diversity of the search. In the mutation block the weights and the best particle obtained until now are mutated. Then, in the recombination block the particles in the swarm share the information to move through the search space. This recombination step uses the usual recombination rule of PSO algorithms according to which a particle move is determined by an inertial, a memory and a cooperation term. The inertia term tends to move the particle in the same direction as in the previous iteration and the memory term models the individual knowledge of the particle because the move is attracted to the position of the best of its ancestors. The cooperation term represents the collective knowledge and it attracts the particle to the best global position obtained so far. The combination of these three terms determines the position of the new particle in the next iteration. All the particles are then evaluated using an OPF model (DC or AC) in each of the periods in the horizon and checking the values of PNS. Non zero PNS values penalize the fitness function of each particle. The values of the fitness function of each particle in each clone are then used in the selection block to run an elitist selection. Detailed information on the DEPSO algorithm is available in [3].

V. Tests and Results

The CHA and the DEPSO tools were applied to 3 different test systems indicated below. Case 6 and Case 30 Bus test systems are available in version 5.1 of the MATPOWER tool described in [5] and the third system is a modified version of the IEEE RTS 24 bus system. The objective was to analyze if the CHA reduces the search space not eliminating routes that are used in the optimal final expansion plan and to analyze if the solutions using the DC based dispatch model do not violate constraints of the AC model. The simulation were performed in Matlab® with an Intel i7, 3.4GHz, 8 GB RAM.

Regarding the power flow solution, the maximum allowed flow was considered in emergency condition for all branches and the loads are modeled as dispatchable loads, that is, as negative real power injections with associated negative costs as detailed in [6].

The tests were performed using the multiyear TEP model with 3 periods and admitting a 5% load increase per period. DEPSO was run using 150 particles in the swarm, the PNS penalty factor used in (1) was set at $\beta = 10^{12}$. The DEPSO algorithm stops when the best particle does not change after running 50 iterations. Finally, the P communication factor that controls the cooperation term in the DEPSO recombination rule was set at 1 as in classical applications.

A. Case 6 Bus Test System

The investment cost for each branch was taken as proportional to capacity of that branch and the generation capacity and loads are tripled to turn the grid more stressed. The results of the simulations are described below.

- Reduction of the search space

The CHA was used in the Case 6 bus test system and was applied in AC-OPF and DC-OPF. In both cases the process took less than 1 minute and the results are shown in Table I.

TABLE I. REDUCTION IN THE CASE 6 BUS TEST SYSTEM

MODEL	EQUIPMENT
AC OPF	1-4, 1-5, 2-4, 3-6
DC OPF	2-4, 2-5, 3-5, 3-6

- Solutions obtained using the entire search space

DEPSO was applied to the Case 6 bus using the AC and DC approaches. In the AC-OPF model the process solved 283053 OPFs and in DC version solved model 198453 OPFs. The results obtained are shown in Table II.

TABLE II. DEPSO APPLIED TO THE CASE 6 BUS - ENTIRE SEARCH SPACE

MODEL	PERIOD	EQUIPMENT	INV. COST (€)
AC OPF	1	1-4, (2) 1-5, (3) 2-4, (2) 2-5, (2) 2-6, 3-5, (2) 3-6	790.10^6
	2	3-5	70.10^6
	3	1-2, 1-4, (2) 2-3	180.10^6
DC OPF	1	(3) 1-5, (2) 2-4, 3-6	390.10^6
	2	3-5	70.10^6
	3	1-2, 1-4, 4-5, (2) 5-6	200.10^6

- Solutions obtained with the reduced search space

The DEPSO was also applied to Case 6 bus using the AC and the DC-OPF using the reduced search space. In the first case the process solves 110253 AC-OPFs and in the second case 92253 DC-OPFs. The results are shown in Table III.

TABLE III. DEPSO APPLIED TO THE CASE 6 BUS - REDUCED SEARCH SPACE

MODEL	PERIOD	EQUIPMENT	INV. COST (€)
AC OPF	1	(3) 1-4, (3) 1-5, (3) 2-4, (3) 3-6	720.10^6
	2	---	0
	3	---	0
DC OPF	1	(2) 2-4, 3-5, (2) 3-6	350.10^6
	2	---	0
	3	2-4, (2) 2-5, 3-5	540.10^6

B. Modified IEEE RTS 24 Bus

In this case we used the modified IEEE 24 Bus RTS system that has some differences regarding the original one proposed in [8]. The details of this modified system can be found in [3] and [6]. The results of the simulations are described as follows.

- Reduction of the search space

The CHA was used in the modified 24 Bus RTS test system using the AC-OPF and the DC-OPF. In both cases the process took less than 1 minute, the obtained results are shown in Table IV.

TABLE IV. REDUCTION IN THE MODIFIED 24 BUS SYSTEM

MODEL	EQUIPMENT
AC OPF	1-5, 3-24, 6-10, 7-8, 11-13, 13-23, 14-16, 15-24, 16-17, 17-18
DC OPF	3-24, 6-10, 7-8, 11-13, 14-16, 16-17

- Solutions obtained Using the entire search space

DEPSO was applied to the modified 24 bus using the AC and the DC approaches. In the AC-OPF model the process solved 123906 OPFs and in DC-OPF model 277653 OPFs. The results are shown in Table V.

TABLE V. DEPSO APPLIED IN THE MODIFIED 24 BUS SYSTEM – ENTIRE SEARCH SPACE

MODEL	PERIOD	EQUIPMENT	INV. COST (€)
AC OPF	1	6-10, 7-8, 14-16	86.10^6
	2	---	0
	3	9-11, 10-12, 15-21	236.10^6
DC OPF	1	6-10, 14-16	70.10^6
	2	---	0
	3	1-3, (2) 15-21, 19-20, 21-22	531.10^6

- Solutions founded on the reduced search space

The DEPSO was also applied in modified 24 bus using AC and DC-OPF using the entire search space solving 101103 and 142653 OPFs respectively. The results obtained are shown in table VI below:

TABLE VI. DEPSO APPLIED TO THE MODIFIED 24 BUS SYSTEM – REDUCED SEARCH SPACE

MODEL	PERIOD	EQUIPMENT	INV. COST (€)
AC OPF	1	6-10, 7-8, 14-16	86.10^6
	2	---	0
	3	6-10, 16-17, 17-18	72.10^6
DC OPF	1	6-10, 14-16	70.10^6
	2	---	0
	3	16-17	36.10^6

C. Case 30 Bus Test System

This system was obtained from MATPOWER version 5.1 and its generation capacities and loads were also tripled.

- Reduction of the search space

The CHA was used in the Case 30 Bus test system applying the AC-OPF and the DC-OPF. In both cases the process took less than 1 minute and the obtained results are shown in Table VII.

TABLE VII. REDUCTION IN THE CASE OF THE 30 BUS TEST SYSTEM

MODEL	EQUIPMENT
AC OPF	2-6, 6-8, 21-22, 22-24, 27-30
DC OPF	2-6, 6-8, 12-13, 15-18, 10-20, 21-22, 23-24, 25-27, 27-30

- Solutions obtained using the entire search space

DEPSO was applied in the Case 30 bus using the AC and the DC approaches. In this case 389253 and 245253 OPFs are solved respectively. The results are shown in Table VIII.

TABLE VIII. DEPSO APPLIED IN THE CASE 30 BUS – ENTIRE SEARCH SPACE

MODEL	PERIOD	EQUIPMENT	INV. COST (€)
AC OPF	1	2-6, (3) 6-8, 10-20, 10-22, 15-23, (2) 21-22, 27-29	353.10^6
	2	4-12, 6-10, 6-28, 27-28, (2) 29-30	210.10^6
	3	(2) 1-2, 2-5, 3-4, 4-6, 4-12, 6-7, 6-9, 8-28, 9-10, 10-21, 10-22, (2) 12-14, 12-15, (2) 12-16, 15-18, 19-20, 25-26	1255.10^6
DC OPF	1	2-6, (2) 6-8, 21-22, 27-30	177.10^6
	2	15-18, 15-23	32.10^6
	3	1-2, (2) 3-4, 5-7, 8-28, 12-16, 29-30	540.10^6

- Solutions obtained using the reduced search space

The DEPSO was also applied in Case 30 Bus test system using the AC and the DC-OPF on the reduced search space. In this case 115653 and 117453 OPFs are solved respectively. The results obtained are shown in table IX below.

TABLE IX. DEPSO APPLIED IN THE CASE 30 BUS – REDUCED SEARCH SPACE

MODEL	PERIOD	EQUIPMENT	INV. COST (€)
AC OPF	1	(3) 2-6, (3) 6-8, (2) 21-22, (3) 22-24, 27-30	419.10^6
	2	---	0
	3	21-22, (2) 27-30	64.10^6
DC OPF	1	2-6, (2) 6-8, 21-22, 27-30	177.10^6
	2	10-20	32.10^6
	3	2-6, (2) 12-13, 25-27, 27-30	227.10^6

TABLE X. QUALITY SOLUTION ANALYSIS – DC-OPF MODEL

TEST SYSTEM	SOLUTION FOUNDED USING DC-OPF	PNS IN AC-OPF (MW)
Case 6 bus	REDUCED SEARCH SPACE	533,07
	ENTIRE SEARCH SPACE	462,10
RTS 24 bus	REDUCED SEARCH SPACE	465,64
	ENTIRE SEARCH SPACE	448,51
Case 30 bus	REDUCED SEARCH SPACE	199,05
	ENTIRE SEARCH SPACE	213,63

D. Evaluation of the quality of the DC solution

In order to evaluate the solution quality of the DC model, the DC solutions are checked using the AC-OPF. The results obtained are shown in Table X.

VI. CONCLUSIONS

In this paper a multi-year Transmission Expansion Planning was conducted using AC and DC optimal power flow models. Besides, the Constructive Heuristic Algorithm presented in Section III was applied to reduce the search space using the AC and DC model. The simulations were performed in three different test systems termed as Case 6 bus and Case 30 bus from version 5.1 of the MATPOWER tool and the modified IEEE RTS 24 Bus from [3].

Regarding the search space reduction exercise, from the results presented in the above section, the AC model shows excellent performance in all three test systems since it was able to ensure that the best branches were included in the reduced search space, that is, the branches that belong to the best expansion plan were maintained in the search space after the reduction. On the other hand, the CHA using the DC model does not present this type of performance.

The results obtained using the DC model were then input on the AC to check if there were violations of AC constraints. In all cases, the best DC solution has non zero PNS when using the AC model. These results are in line with the results reported in [2], that is, TEP approaches using the DC models are likely to present violations using the AC model.

ACKNOWLEDGMENT

P. Vilaça acknowledges the financial support from CAPES Scholarship under Bex 13207-13-0.

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B.0.4 Hybrid discrete evolutionary pso for ac dynamic transmission expansion planning. (IEEE International Energy Conference, 2016)

Hybrid Discrete Evolutionary PSO for AC Dynamic Transmission Expansion Planning

Phillipe Vilaça Gomes
INESC TEC and FEUP/DEEC
Dept. Eng. Eletrotécnica e de Computadores da Faculdade de Engenharia da Universidade do Porto
Porto, Portugal
phillipe.gomes@fe.up.pt

João Tomé Saraiva
INESC TEC and FEUP/DEEC
Dept. Eng. Eletrotécnica e de Computadores da Faculdade de Engenharia da Universidade do Porto
Porto, Portugal
jsaraiva@fe.up.pt

***Abstract* —Multiyear Transmission Expansion Planning (TEP) aims to determine how and when a transmission network capacity should be expanded taking into account an extended horizon. This is an optimization problem very difficult to solve and that has unique characteristics that increase its complexity such as its non-convex search space and its integer and nonlinear nature. This paper describes a hybrid tool to solve the TEP problem, including a first phase to select a list of equipment candidates conducted by a Constructive Heuristic Algorithm (CHA), and a second phase that uses Discrete Evolutionary Particle Swarm Optimization (DEPSO) for the final planning. Both phases use the AC power flow model as a way to improve the realism of the developed tool. The paper includes a case study based on the IEEE 24-Bus Reliability Test System and the results show that tools based on swarm intelligence applied to reduced search spaces are able to find good quality solutions with low computational effort.**

***Index Terms* — Multiyear Transmission Expansion Planning, DEPSO, Search Space Reduction, AC Optimal Power Flow.**

I. Introduction

The increasing demand for electricity and the changes in its consumption profile, with the introduction of distributed generation and micro grids for example, require a thorough analysis of how the system should evolve along an extended period of time. In this scope and using pre-defined list of candidate equipment (transmission lines, cables, transformers, etc) to be inserted on the grid, Transmission Expansion Planning (TEP) has the purpose of identifying the ones to be built and their commissioning date to minimize the operation and investment costs while supplying the forecasted demand. Furthermore, the transmission planning analysis must also take into account issues as security and reliability, which makes it a very complex problem.

TEP models and approaches can be classified as static or dynamic (multi-year). Regarding static approached, each period is considered at a time and equipment selected in a given period is considered as available on the next one. Dynamic approaches take the horizon in a holistic way and the problem is solved at a single run because we aim at identifying the equipment to be built as well as locating them along sub periods. It is noteworthy that when the TEP is done dynamically the holistic planning view is preserved and this is essential for long-term actions.

Regarding the optimization model that is incorporated in TEP models, we can choose among 3 alternatives:

- Deterministic Model: it includes a set of predicted values for specific variables and these are considered immutable, as generation, demand, market behavior, etc. This model provides an unique expansion planning solution [1].
- Probabilistic Model: The forecasts admit probabilistic randomness and allow working with different scenarios. Obviously, this approach is closer to reality and its solutions are interpreted as estimates of the true system characteristics [2].
- Uncertainty Model: This type of models admit that some uncertain data are affected by lack of complete knowledge and this incomplete information is usually modeled with fuzzy numbers [3].

Generally, the TEP problem considers the expansion cost as its objective function to be minimized. However, it can also be formulated using other objectives as alleviating transmission congestion, minimizing the risk associated to the investments, increasing the reliability of the network, increasing the flexibility of system operation while reducing the network charges, minimizing the environmental impacts or providing a better voltage profile.

Besides, TEP has some peculiarities that increase its difficulty in terms of developing new tools such as:

- Non-convex search space, so that solution algorithms may converge to local optima;
- Integer nature leading to the phenomenon of combinatorial explosion of investment alternative plans which in turn requires a high computational effort to identify good quality plans;

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- In some cases there are isolated smaller systems, which can lead to convergence problems.

Given the difficulties mentioned above, several tools have been proposed in the literature for its solution. Usually these tools are organized into three large groups: Classical Optimization [4], Constructive Heuristic Algorithms (CHA), [5] and Metaheuristics [6]. The first one is able to find optimal and sub-optimal solutions for small systems, but requires a high computational effort that usually turns its application prohibitive in realistic problems. Constructive Heuristics are able to find acceptable solutions through a low computational effort, and Metaheuristic algorithms are usually based on nature patterns, corresponding to powerful tools that are able to find optimal solutions and sub-optimal through a typically large computational effort.

Metaheuristics based on swarm intelligence are reported to show good behavior to solve the TEP problem. This kind of technique has even better results when the particles are initialized in a good position in the search space and if the number of expansion alternatives are drastically reduced [1]. On the other hand, the integer behavior of the problem requires a more accurate modeling of the swarm. This justifies the use of Discrete Evolutionary Particle Swarm Optimization (DEPSO) described in [6] given the good performance in solving problems with non-continuous and integer search spaces.

The hybrid DEPSO will be introduced in this paper to the multiyear and deterministic TEP problem. Therefore, TEP was addressed in a hybrid way, considering in two phases as follows: The first one uses a CHA to select a reduced number of candidate equipment from an initial larger list and the second phase uses the DEPSO to build and refine the final solution. This approach was developed using the AC power flow (AC-OPF) operation model, bearing in mind the gap between the AC and DC models [7].

Regarding the structure of the paper, following this Introduction, Section II presents the AC model used in the scope of the TEP problem and Section III provides a brief description of the Constructive Heuristic Algorithm, CHA, that was adopted in the developed methodology. Section IV details the Discrete Evolutionary Particle Swarm Optimization, DEPSO, and Section V presents the results obtained in the simulations. Finally Section VI includes some comments and provides the conclusions about this work

II. TEP Mathematical Formulation

The optimization techniques used to solve the AC model must be extremely efficient to deal with the required computational effort. On the other hand, the AC model takes into account the reactive power, the losses and the voltage limits on the bars, which makes this model more adequate and realist to reflect the operation conditions of the network and therefore to estimate the operational cost of a power system.

The AC-OPF used in this paper is formulated by (1) to (9).

$$\text{Min } C_{OP} = \sum \alpha_{i1}.P_i^2 + \alpha_{i2}.P_i + \alpha_{i3} \quad (1)$$

subject to

$$P(V,\theta,n) - P_G + P_D = 0 \quad (2)$$

$$Q(V,\theta,n) - Q_G + Q_D = 0 \quad (3)$$

$$P_{G\min} \le P_G \le P_{G\max} \quad (4)$$

$$Q_{G\min} \le Q_G \le Q_{G\max} \quad (5)$$

$$V_{\min} \le V \le V_{\max} \quad (6)$$

$$(N + \overset{o}{N})S^{from} \le (N + \overset{o}{N})S_{\max} \quad (7)$$

$$(N + \overset{o}{N})S^{to} \le (N + \overset{o}{N})S_{\max} \quad (8)$$

$$0 \le n \le n_{\max} \quad (9)$$

In this formulation $P(V,\theta,n)$ and $Q(V,\theta,n)$ are calculated by (10) and (11), and the bus conductance G and susceptance B are given by (12) and (13).

$$V_i \sum V_j [G_{ij}(n).\cos\theta_{ij} + B_{ij}(n).\sin\theta_{ij}] \quad (10)$$

$$V_i \sum V_j [G_{ij}(n).\sin\theta_{ij} - B_{ij}(n).\cos\theta_{ij}] \quad (11)$$

$$G = \begin{cases} G_{ij}(n) = -(n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \\ G_{ii}(n) = \sum_{j\in\Omega_i} (n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \end{cases} \quad (12)$$

$$B = \begin{cases} B_{ij}(n) = -(n_{ij}.b_{ij} + \overset{o}{n}_{ij}.\overset{o}{b}_{ij}) \\ B_{ii}(n) = b_{ij}^{sh} + \sum_{j\in\Omega_i} [n_{ij}(b_{ij} + b_{ij}^{sh}) + \overset{o}{n}_{ij}(\overset{o}{b}_{ij} + \overset{o}{b}_{ij}^{sh})] \end{cases} \quad (13)$$

The apparent flows S^{from} and S^{to} are calculated by (14) and (15) where P_{ij}^{from}, Q_{ij}^{from}, P_{ij}^{to} and Q_{ij}^{to} are given by (16) to (19).

$$S_{ij}^{from} = \sqrt{(P_{ij}^{from})^2 + (Q_{ij}^{from})^2} \quad (14)$$

$$S_{ij}^{to} = \sqrt{(P_{ij}^{to})^2 + (Q_{ij}^{to})^2} \quad (15)$$

$$P_{ij}^{from} = V_i^2.g_{ij} - V_i V_j (g_{ij}.\cos\theta_{ij} + b_{ij}.\sin\theta_{ij}) \quad (16)$$

$$Q_{ij}^{from} = -V_i^2.(b_{ij}^{sh} + b_{ij}) - V_i V_j (g_{ij}.\sin\theta_{ij} - b_{ij}.\cos\theta_{ij}) \quad (17)$$

$$P_{ij}^{to} = V_j^2.g_{ij} - V_i V_j (g_{ij}.\cos\theta_{ij} - b_{ij}.\sin\theta_{ij}) \quad (18)$$

$$Q_{ij}^{to} = -V_j^2.(b_{ij}^{sh} + b_{ij}) + V_i V_j (g_{ij}.\sin\theta_{ij} + b_{ij}.\cos\theta_{ij}) \quad (19)$$

In the objective function (1) α_{i1}, α_{i2} and α_{i3} are coefficients of the quadratic generator cost function. P_G is the real power generation, Q_G is the reactive power generation, P_D is the real power demand, Q_D is the reactive power demand, V is the voltage magnitude, S^{from} and S^{to} are the branch apparent flows in both terminals, g_{ij} and b_{ij} are the conductance and the susceptance of branch i-j, N_o and N are diagonal matrices containing the equipment in the base topology and the added equipment respectively

III. Multi-year Approach

TEP Multi-year has the objective of minimizing the total system costs, that is, the sum of operating and investment costs, brought to the present as shown in (20).

$$fitness = \sum_{p=1}^{np} \frac{(C_{INV,p} + C_{OP,p})}{(1+r)^p} + \beta.PNS \qquad (20)$$

In this equation, np is the number of considered periods, $C_{INV,p}$ is the investment cost in period p given by (21), r is the return rate, and β_1 is the penalty factor for Power Not Supplied (PNS). In (21) c_{ij} is the cost of installing a network equipment in path i-j and η_{ij} is the number of equipment of that type to install in parallel in that path.

$$C_{INV} = \sum c_{ij}.n_{ij} \qquad (21)$$

The dynamic multi-year approach for the TEP problem involves solving a problem of greater complexity due to the combinatorial explosion much larger than in the static or single period problems. In single period approaches the goal is to minimize the operation and investment costs for the specific year under analysis while in multi-year approaches it becomes the minimization of the sum of all costs along the extended planning horizon. This holistic view allows the problem to eventually select an investment alternative that is more expensive in a particular period, but that has advantages and becomes cheaper when the whole set of periods in the horizon are considered.

IV. Constructive Heuristic Algorithm

The Constructive Heuristic Algorithms (CHA) are tools that use a function as a sensitivity criterion to assess the system performance and iteratively build solutions, in the sense that at each iteration new additions are included as a way to obtain the final solution. These characteristics typically enable CHAs to have low computational effort and reasonable efficiency. The CHAs have been proposed to solve the TEP problem since the 70's by several authors [8], [9].However it continues to be used mainly incorporated in hybrid tools in which the mentioned characteristics are used in a profitable way to reduce the search space of the TEP problem [1], [10].

At each iteration, the CHA uses a sensitivity criterion having local nature to assess the most adequate equipment to allow a power system to operate properly, that is, without PNS. The search space reduction is obtained via the list of candidate equipment that forms its final output. The equipment in this list is then taken as input to a second phase of the TEP algorithm to build the final expansion plan.

In this paper it was used the Least Effort CHA proposed by [11] to select a list of equipment to be candidates to be built and included in the transmission system. This list is a subset of a wider set of possible equipment and so the CHA promotes a reduction of the search space of the TEP problem. In this CHA the sensitivity function used evaluate the interest in having a specific equipment in this subset is the power flow in the equipment, that is, at each iteration the most congested equipment is included in the subset until the PNS is canceled. Fig. 1 displays the main steps of the iterative process of the Least Effort CHA.

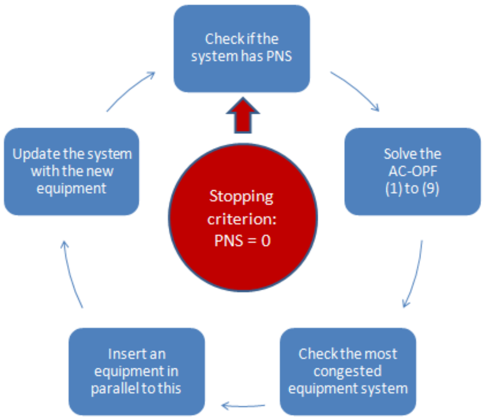

Figure 1: Least Effort CHA – Iterative process.

When this iterative process ends, the CHA provides a list of equipment that will be considered as the input to the DEPSO algorithm, that is, as the list of equipment candidates from which a final combination will be extracted and organized as the solution to the TEP problem.

V. Discrete Evolutionary Particle Swarm Optimization

The DEPSO was developed by Rocha and Saraiva [12] in 2011 and its main objective was to adapt the EPSO to solve problems with non-continuous and integer search spaces as the TEP problem. Basically, this tool combines some concepts of evolutionary computation and multi agent population, using the standards blocks that are typical in Genetic Algorithm and Particle Swarm Optimization.

In this tool the population is formed by a set of particles that carry information about the projects for the system expansion. Each particle is encoded using integer numbers which represent the period in which a particular equipment will be inserted into the network. If the position of a particular equipment in a particle has the number 0 then this equipment is not used in the expansion planning. Therefore, considering the dynamic TEP problem discretized in np periods, there are np + 1 integer numbers (from 0 to np) that can be associated to each equipment. Fig. 2 shows a coding example regarding a list of 5 candidate equipment. In this case, this particle includes information about the time allocation of equipment 1, 2, 3, and 5 to each of the 3 periods while equipment 4 is not included in the plan associated to this particle.

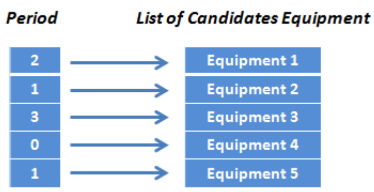

Figure 2: Illustration of the particle codification.

In this example, equipment 2 and 5 will be inserted in the first period, equipment 1 will be built in the second period and equipment 3 in the last period. Equipment 4 was not included in this plan.

According to this coding strategy, each particle is represented by a vector with N_{proj} positions – amount of equipment in the list of candidates. Since each position is filled with an integer from 0 to np, then the size of the search space (SSS) is defined by (22).

$$SSS = (np+1)^{nproj} \tag{22}$$

The main DEPSO blocks are presented below:

Procedure DEPSO
Set the list of candidate equipment having N_{proj}elements
Initialize a random population with ps particles
Repeat
    Replication
    Mutation
    Recombination
    Evaluation
    Selection
    Stop Test
Until test is positive
End DEPSO

In the Replication block the population is cloned r times. Then according the ideas proposed in [12] , in the Mutation block the weights and the best particle until now (that will be used in Recombination Block) are mutated using equations (23) and (24) in which the symbol * represents the mutation and rand() is a random number between 0 and 1.

$$\overset{*}{w}_{ij}^{it+1} = 0{,}5 + rand() - \frac{1}{1+\exp(-\overset{*}{w}_{ij}^{it})} \tag{23}$$

$$\overset{*}{gbest} = gbest + round(2.\overset{*}{w}_{i4}^{it+1} - 1) \tag{24}$$

In (23) j=1 to 4 so that this expression is used to mutate the four weights used in the algorithm and i is the index associated to a particle. Accordingly, for j=1, $\overset{*}{w}_{i1}^{it+1}$ is the weight conditioning the inertia term, for j=2 $\overset{*}{w}_{i2}^{it+1}$ is the weight conditioning the memory of each particle (reflecting its history and individual knowledge), for j=3 $\overset{*}{w}_{i3}^{it+1}$ is the weight conditioning the cooperation inside the swarm (associated to the collective knowledge of the swarm) an finally for j=4 $\overset{*}{w}_{i4}^{it+1}$ is the term that is used to mutate the gbest particle, that is, the best particle founded until the current iteration.

In the Recombination block new offsprings are created for each particle of cloned population using the EPSO movement rule for each particle i and rounding up the value obtained for each position in the vector to integers, as described by (25) and (26) and illustrated in Fig. 3.

$$V_i^{it+1} = \overset{*}{w}_{i1}^{it+1}.V_i^{it} + \overset{*}{w}_{i2}^{it+1}.(pbest_i - X_i^{it}) + \overset{*}{w}_{i3}^{it+1}.(gbest - X_i^{it}).P \tag{25}$$

$$X_i^{it+1} = X_i^{it} + V_i^{it+1} \tag{26}$$

The first term in (25) represents the inertia of the particle, that is, its trend to follow its previous movement, the second term represents its individual knowledge, that is, it induces a movement towards the best position that was found so far for this particle and, finally, the last term represents the collective knowledge of the swarm in the sense that it is introduced a component to move the particle towards the best particle so far identified in the entire swarm. P is the communication factor described in [13]. It typically takes values 0 or 1 so that if 0 is used for a position of the particle vector then the collective knowledge is not passed to this particle in the next iteration.

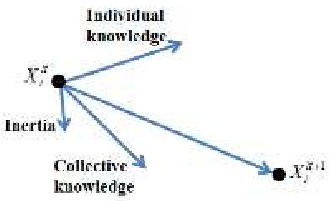

Figure 3: Particle movement in typical PSO algorithms.

If the velocity of some particle is zero this would mean that particle would not move from one iteration to another. However, to introduce more diversity and following again the approach described in [3, 12], a Lamarckian evolution with symmetric probability is applied according with (26). This means that the particle would not move because microscopic or genotype changes given by (25) were insufficient but a change at the macroscopic or phenotype level was introduced in order to reach more perfect and adapted solutions. This borrows the ideas of the French biologist Baptiste Lamarke that is often considered as a proto evolutionist.

$$V_i^{it+1} = round(np.(0{,}5 + rand() - 1)) \tag{26}$$

When the new position of a particle is out of the search space, that is in some of its positions the values are larger or smaller than the maximum or minimum values, then the particle is returned back to the search space by setting at 0 the values smaller than 0 and by sampling a value smaller or equal to np if the original value was larger than np (27).

$$X_i^{it+1} = np - round(rand()) \tag{27}$$

After the Recombination step, the offsprings are evaluated using (20). Finally, the selection is made through an elitist process. In this step recall that we have r clones each of them having ps particles. The selection procedure takes the first particle of each r clone and it survives the one that has the best fitness function. This procedure is repeated for all ps particles so that at the end a new population is created having the same size of the initial one and the values of gbest and pbest are updated. The process ends when gbest does not change after running a pre specified number of iterations.

VI. Tests and Results

The system used to test the developed TEP approach is the modified IEEE 24 BUS RTS system. This system has some differences regarding the original one proposed in [14] as described below:

- Maximum allowed flow in emergency condition for all branch;
- The loads are modeled as negative real power injections with associated negative costs as described in [15]. This modeling is performed using a negative output generator, ranging from a minimum injection equal to the negative total load to a maximum injection of zero. This means the AC OPF problem has enough flexibility to reduce the demand if that is required to maintain feasibility. Additionally, if a particular nodal real load is not entirely supplied then the reactive demand is also reduced in the same proportion as a way to keep the power factor of the original load unchanged.
- Reactive power sources are located in particular buses, as suggested in [16] and according to Table I;
- The values of all loads and of the installed capacity of all generators were tripled (real and reactive) in order to turn the network more stressed and the maximum voltage variation was set at 10%.

TABLE I. VOLTAGE CORRECTION DEVICES

VOLTAGE CORRECTION DEVICES			
DEVICE	BUS	MVAR	CAPABILITY
SYNCH. CONDENSER	3	350	CAPACITIVE
SYNCH. CONDENSER	9	510	CAPACITIVE

The tests were performed considering the multiyear TEP model with 3 periods and using a load increase of 5% per period. The Least Effort CHA was applied to select a list of candidate equipment considering a static TEP problem for each period. After solving 23 AC-OPFs, using the MATPOWER tool described in [15], running in MATLAB with an Intel i7, 3.4GHz, 8 GB RAM, the output of the CHA is given in Table II.

It is important to note that the majority of papers existing in TEP literature consider that the branches of the departing topology are also candidates with a maximum number of additions usually set at 3. The excessive number of elements in the candidate list may cause the computational effort to be so large that it prevents or turns it very difficult to solve the problem. Using the CHA proposed in this paper, to build a subset of candidate equipment taken from the large initial list promotes the reduction of the search space by 99.99% from $(3+1)^{38} \approx 10^{23}$ to $(3+1)^{19} \approx 10^{11}$.

After this initial step, DEPSO was run using 100 particles in the swarm, PNS penalty factor used in (20) $\beta = 10^{12}$, 50 iterations with the same gbest as stopping criterion and P communication factor equal to one as in classical formulations. DEPSO solved 68724 AC-OPFs in about 3.4 hours achieving the best solution after running 57 iterations. This solution is displayed in Table III and Figure 4 displays the evolution of the fitness function (20) of the best particle.

TABLE II. OUTPUT LIST OF EQUIPMENTS OF THE CHA ALGORITHM

no.	Equipment
1	138 kV line connecting bus 1 to 5
2	138 kV line connecting bus 1 to 5
3	Transformer between bus 3 and 24
4	Transformer between bus 3 and 24
5	138 kV cable connecting bus 6 to 10
6	138 kV cable connecting bus 6 to 10
7	138 kV line connecting bus 7 to 8
8	138 kV line connecting bus 7 to 8
9	138 kV line connecting bus 7 to 8
10	230 kV line connecting bus 14 to 16
11	230 kV line connecting bus 14 to 16
12	230 kV line connecting bus 14 to 16
13	230 kV line connecting bus 15 to 24
14	230 kV line connecting bus 15 to 24
15	230 kV line connecting bus 16 to 17
16	230 kV line connecting bus 16 to 17
17	230 kV line connecting bus 17 to 18
18	230 kV line connecting bus 17 to 18
19	230 kV line connecting bus 20 to 23

TABLE III. BEST SOLUTION IDENTIFIED BY THE DEPSO

Period	New Equipment (no.)	Investment Cost (€)	Operational Cost (€/h)	PNS
1	5, 7, 10	86000000	1549986	0
2	---	0	1745338	0
3	5, 15, 17	72000000	1733134	0

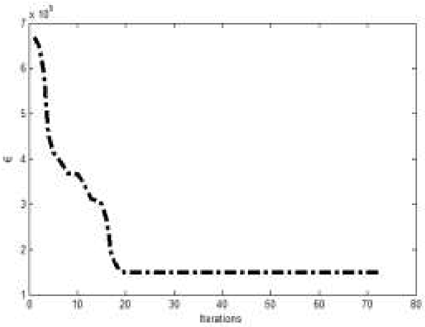

Figure 4: Evolution of the fitness function of the *gbest* particle.

According to this solution, investing in Period 1 in equipment no. 5, 7 and 10 allows the system to gain flexibility enough to accommodate the demand increase in Period 2 so that no new equipment are required in Period 2. New equipment is therefore postponed for Period 3, which decreases the present value of the investment. This solution is the best one that was identified in all simulations.

In order to evaluate the performance of the reducing search space technique in terms of not eliminating equipment that afterwards should be used to build the best solution, DEPSO was also simulated without using the CHA technique described in Section IV. In this simulation the original complete list of 38 equipments was used and the DEPSO parameters were the same as the ones used in the simulation including the CHA (namely the number of particles and the convergence rule). Not using CHA, the best solution also includes 6 equipments. However the total present investment cost is 95% higher than the value of the solution that was obtained using the CHA technique. These equipments are distributed by the three periods as follows – 3 in period 1, 0 in period 2 and 3 in period 3. Comparing this solution with the one obtained using the CHA technique it happens that in periods 1 and 2 the two solutions are similar but in period 3 the solution not using the CHA includes equipments that increase the cost. As a comment to these results, it is clear that the DEPSO by itself was not able to identify the best solution to the problem at least with the parameters that were used. However, when the CHA technique is used prior to the DEPSO, the search space gets reduced, the combinatorial nature of the problem is also reduced and DEPSO is now able to build a higher quality solution. Therefore, using the described CHA shows two advantages. In the first place, it reduces the computational effort to solve the problem given the reduction of the search space. If a solution of comparable quality was to be obtained, then the DEPSO not running the CHA in the first place would certainly require more iterations and thus an increased computation time. Secondly, it does not compromise the quality of the final solution. In fact, DEPSO is now able to build a much better solution given that the combinatorial nature of the problem is reduced.

VII. CONCLUSIONS

This paper presents a hybrid methodology to solve the Dynamic Transmission Expansion Planning Problem. The developed methodology was applied to a modified version of the IEEE 24-Bus Reliability Test System that includes two voltage control devices and the network operating conditions were stressed tripling the generation capacities and the loads.

The developed approach is organized in two stages. In the first one it is used the Least Effort Constructive Heuristic Algorithm to build a reduced list of candidate equipment. This CHA is used for each of the periods in the horizon considering that the demand increases 5% per period. In the second stage the Discrete Evolutionary Particle Swarm Optimization, DEPSO, was applied using the reduced list of candidate equipment as input to build the final expansion plan. In each period the operation of the system was analyzed using an AC-OPF model that was preferred regarding DC based versions in view of the gap between solutions obtained using these two models in the solution of the TEP problem.

This paper is an evolution of the approach described in [1], since a dynamic model is now used and DEPSO replaces the traditional PSO metaheuristic. The major contribution in this paper is twofold – the use of the CHA to reduce the search space as well as the computational effort and the use of both DEPSO and the AC OPF models thus increasing the realism of the solution of the multiyear TEP problem.

ACKNOWLEDGEMENTS

The first author thanks CAPES Foundation, Ministry of Education of Brazil, for financing this research.

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B.0.5 Hybrid genetic algorithm for multi-objective transmission expansion planning.. (IEEE International Energy Conference, 2016)

Hybrid Genetic Algorithm for Multi-Objective Transmission Expansion Planning

Phillipe Vilaça Gomes
INESC TEC and FEUP/DEEC
Dept. Eng. Eletrotécnica e de Computadores da Faculdade de Engenharia da Universidade do Porto
Porto, Portugal
phillipe.gomes@fe.up.pt

João Tomé Saraiva
INESC TEC and FEUP/DEEC
Dept. Eng. Eletrotécnica e de Computadores da Faculdade de Engenharia da Universidade do Porto
Porto, Portugal
jsaraiva@fe.up.pt

***Abstract* — This paper aims to describe a new tool to solve the Transmission Expansion Planning problem (TEP). The Non-Dominative CHA-Climbing Genetic Algorithm uses the standard blocks of Genetic Algorithms (GA) associated with an improvement of the population building block using Constructive Heuristic Algorithms (CHA) and Hill Climbing Method. TEP is a hard optimization problem because it has a non convex search space and integer and nonlinear nature, besides, the difficulty degree can be further increased if it includes more than one objective. In this work, a multi-objective TEP approach is detailed using an AC Optimal Power Flow to generate the set of Pareto solutions using the investment cost and the level of CO_2 emissions, i.e. two conflicting objectives.**

***Index Terms* — Transmission Expansion Planning, Multi-objective approach, Pareto solutions, AC Optimal Power Flow.**

I. Introduction

The global warming in recent decades has been conducting several researchers from different areas to deepen their knowledge on mitigating the emission of greenhouse gases (GHG). According to the International Energy Agency (IEA), the electricity sector has a fundamental importance in this context [1], since it is responsible for about 40% of the CO_2 emissions (in conjunction with heat). As shown in Fig. 1, it is therefore the sector responsible for the largest share of these emissions.

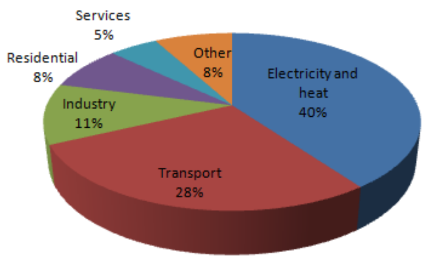

Figure 1: CO_2 emissions by sector in 2013 (Source: IEA)

The large amount of CO_2 emissions associated with the electricity sector can be clearly understood analyzing the graph in Fig.2, in which the world power mix includes about 70% of power stations using fossil fuels [2].

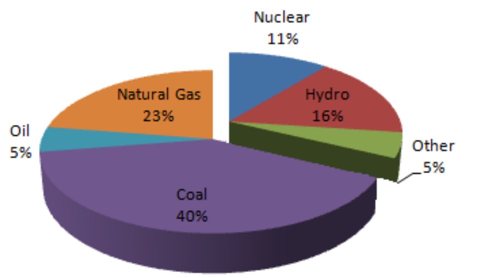

Figure 2: Fuel Share of Electricity Generation in 2012 (Source: IEA)

Therefore, it becomes trivial that the GHG mitigation challenge in the electricity sector is directed to the use of renewable energy sources rather than fossil fuels. Nevertheless in order to enable the increase of the penetration of renewable sources it becomes necessary, in many cases, the construction/ installation of new equipment (transmission lines, cables, transformers, etc) connecting the generating stations to the consumer centers, which means that a long-term transmission expansion planning exercise is in many cases required.

Transmission Expansion Planning (TEP) is one of the most challenging problems in power systems. The goal of this problem is the identification of the branches that should be reinforced or installed (or new paths to be built) and the most adequate schedule to expand them, to increase the power flow transmission capability and to alleviate network congestion. However, solving this problem is an extremely complex task since its search space has a discrete nature. Several solution approaches solve a relaxed continuous version of the original problem that is rounded at the end. This procedure does not ensure the identification of the global optimum. On the other hand, addressing the original discrete problem can lead to the explosion phenomenon in its search space.

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Generally, the TEP problem considers the expansion cost as its objective function to be minimized. However, it can also be using a multi-objective approach and that should attend, among others, to the following objectives:

- Alleviate transmission congestion;
- Minimize the risk associated to the investments;
- Minimize the investment and operation costs;
- Increase the reliability of the network;
- Increase the flexibility of system operation while reducing the network charges;
- Minimize the environmental impacts;
- Allow better voltage level regulation.

In this paper, the TEP problem was modelled with two conflicting objectives: the investment cost and the level of CO_2 emissions. These objectives were considered in the scope of a new tool that is also detailed in this paper: The Non-Dominative CHA-Climbing Genetic Algorithm (NDCCGA). This tool includes the fundamental genetic algorithm blocks and an extra block to improve the population using Constructive Heuristic Algorithms (CHA) and Hill-Climbing (HC) techniques. Apart from that, it also includes a Tabu list to control the population diversity. This approach was developed using the AC power flow operation models, bearing in mind the gap between the AC and DC models [3]. Using this approach Transmission System Operators (TSO) will have more sounded information when analyzing possible solutions to the TEP problem, namely having different values of CO_2 emissions and investments costs.

Regarding the structure of the paper, following this Introduction, Section II presents the AC model for the TEP problem and Section III provides a brief description of the multi-criteria approach. Section IV details the developed NDCCGA tool for this approach and Section V presents the results obtained in the simulations. Finally Section VI includes some comments and provides the conclusions about this work.

II. Mathematical Formulation of The TEP Problem

The AC model is the most adequate model to represent the operation conditions of the network in the scope of the TEP problem, because, it has the following main characteristics:

- It considers the reactive power;
- Losses are inherently included in the approach. If the DC model was used then an estimate of network losses had to be obtained for instance using the approach detailed in [4];
- It takes into account the voltage limits on the bars.

However, the use of the AC model leads to a complex nonlinear programming problem that requires an efficient optimization technique to be solved. The AC model was used in [5]–[7] to solve the TEP problem. In this paper the AC-OPF was conducted using the dispatch merit order related with the CO_2 emissions of each power plant (F_1), so that the planner is concerned with the minimization of these emissions thus leading to the AC-OPF given by (1) to (9).

$$\text{Min } F_1 = \sum E_i . P_{Gi} \tag{1}$$

subject to

$$P(V,\theta,n) - P_G + P_D = 0 \tag{2}$$

$$Q(V,\theta,n) - Q_G + Q_D = 0 \tag{3}$$

$$P_{G\min} \le P_G \le P_{G\max} \tag{4}$$

$$Q_{G\min} \le Q_G \le Q_{G\max} \tag{5}$$

$$V_{\min} \le V \le V_{\max} \tag{6}$$

$$(N + \overset{o}{N}) S^{from} \le (N + \overset{o}{N}) S_{\max} \tag{7}$$

$$(N + \overset{o}{N}) S^{to} \le (N + \overset{o}{N}) S_{\max} \tag{8}$$

$$0 \le n \le n_{\max} \tag{9}$$

In this formulation $P(V,\theta,n)$ and $Q(V,\theta,n)$ are calculated by (10) and (11), and the bus conductance G and susceptance B are given by (12) and (13).

$$V_i \sum V_j [G_{ij}(n).\cos\theta_{ij} + B_{ij}(n).\sin\theta_{ij}] \tag{10}$$

$$V_i \sum V_j [G_{ij}(n).\sin\theta_{ij} - B_{ij}(n).\cos\theta_{ij}] \tag{11}$$

$$G = \begin{Bmatrix} G_{ij}(n) = -(n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \\ G_{ii}(n) = \sum_{j\in\Omega_i} (n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \end{Bmatrix} \tag{12}$$

$$B = \begin{Bmatrix} B_{ij}(n) = -(n_{ij}.b_{ij} + \overset{o}{n}_{ij}.\overset{o}{b}_{ij}) \\ B_{ii}(n) = b_{ij}^{sh} + \sum_{j\in\Omega_i} [n_{ij}(b_{ij} + b_{ij}^{sh}) + \overset{o}{n}_{ij}(\overset{o}{b}_{ij} + \overset{o}{b}{}_{ij}^{sh})] \end{Bmatrix} \tag{13}$$

The apparent flows S^{from} and S^{to} are calculated by (14) and (15) where P_{ij}^{from}, Q_{ij}^{from}, P_{ij}^{to} and Q_{ij}^{to} are given by (16) to (19).

$$S_{ij}^{from} = \sqrt{(P_{ij}^{from})^2 + (Q_{ij}^{from})^2} \tag{14}$$

$$S_{ij}^{to} = \sqrt{(P_{ij}^{to})^2 + (Q_{ij}^{to})^2} \tag{15}$$

$$P_{ij}^{from} = V_i^2.g_{ij} - V_i.V_j(g_{ij}.\cos\theta_{ij} + b_{ij}.\sin\theta_{ij}) \tag{16}$$

$$Q_{ij}^{from} = -V_i^2.(b_{ij}^{sh} + b_{ij}) - V_i.V_j(g_{ij}.\sin\theta_{ij} - b_{ij}.\cos\theta_{ij}) \tag{17}$$

$$P_{ij}^{to} = V_j^2.g_{ij} - V_i.V_j(g_{ij}.\cos\theta_{ij} - b_{ij}.\sin\theta_{ij}) \tag{18}$$

$$Q_{ij}^{to} = -V_j^2.(b_{ij}^{sh} + b_{ij}) + V_i.V_j(g_{ij}.\sin\theta_{ij} + b_{ij}.\cos\theta_{ij}) \tag{19}$$

In the objective function (1) E_i represents the CO_2 emission rate for generator i, P_G is the real power generation, Q_G is the reactive power generation, P_D is the real power demand vector, Q_D is the reactive power demand vector, V is the voltage magnitude vector, $S^{to,from}$ are the apparent power flow vectors in the branches in both terminals, g_{ij} is the conductance in branch i-j and b_{ij} is the susceptance in branch i-j.

Apart from the level of CO_2 emissions, each solution to the TEP problem is also characterized by the operation cost given by (20) and the investment cost calculated by (21). In these expressions α are coefficients of a generator cost function, c_{ij} is the cost to install a network equipment in path i-j and η_{ij} is the number of equipments of that type to install in parallel in that path.

$$F_2 = \sum \alpha_{i1}.P_i^2 + \alpha_{i2}.P_i + \alpha_{i3} \quad (20)$$

$$F_3 = \sum c_{ij}.n_{ij} \quad (21)$$

As indicated before, the multi-objective problem is formulated using objectives F1 (level of emissions) and F3 (investment cost). In the current application, the operation cost is used to evaluate the feasibility of each solution because if a non-zero Power Not Supplied value occurs, then the F2 value is highly penalized and the corresponding solution is be most likely discarded in the scope of the Genetic Algorithm to be detailed in Section IV.

It is important to note that the DC model has been widely used because of the larger computational effort involved with the AC model. However, in recent years computer processors experienced an exponential technological advance, dramatically decreasing the processing time. In addition, some researchers reported a gap between DC based and AC models, even if heuristic approaches are used to cope with the increased complexity of AC models. According to [3] TEP solutions obtained using DC based models can significantly underestimate the expansion cost and are eventually unfeasible if they are analyzed using a complete AC power flow model.

III. Multi-Criteria Approach

As previously mentioned, TEP problem usually has more than one objective to be achieved. However the large majority of papers in the literature addresses the problem with only one goal. The multi-objective approach requires further analysis of the problem and the use of techniques that enable the approach since the problem presents a combinatorial nature that can easily lead to the well known the combinatorial explosion phenomenon of discrete problems.

In the approach described in this papers the objectives are the minimization of the investment cost (F_3) for a particular system expansion project and the minimization of the CO_2 emissions (F_1) during the operation horizon. So in addition to the transmission expansion planning, this approach allows to estimate the CO_2 emissions level as well as the future operation costs.

The concept of dominance was used in the NDCCGA tool, for this particular case, with two objectives, the minimization of F_1 and the minimization of F_3. In this scope, a solution x_i dominates a solution x_j ($x_i \triangleright$) when:

$$x_i \triangleright \quad (x_i) \le F_1(x_j) \wedge F_3(x_i) \le F_3(x_j) \quad (22)$$

As will be reported in the next section, the NDCCGA tool aims at building the set of non-dominated solutions, that is, the so called Pareto front.

IV. Non Dominative CHA-Climbing Genetic Algorithm To Build The Pareto Front

The main blocks of the NDCCGA are similar to the ones of a genetic algorithm [8] applied to the solution of the TEP problem. Additionally, it includes an improvement population block and a Tabu list to control the diversity of the population. The population is composed of several individuals, each individual correspond to an expansion plan project in which each gene refers to the number of equipments to be constructed in a given path, and every individual is composed of a set of genes, as show in Fig. 3.

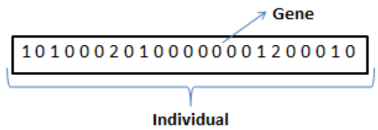

Figure 3: Representation in NDCCGA.

The initial population is randomly created and is ensured its diversity through a Tabu list. After this stage, the individuals will be evaluated according to the AC-OPF and each individual has its characteristics stored (expansion cost, operating cost, PNS and emission level).

Then, individuals will pass through the improvement block, in which individuals having PNS larger than a specified threshold will be improved by CHA and individuals having PNS within the allowed limits will be improved by the Hill Climbing method.

In the reproduction phase, different individuals are randomly grouped in pairs and their genes are exchanged in order to create two offspring. After that, these two offsprings are evaluated calculating the Operation Cost eventually penalized if PNS is not zero. The offspring having the lower Operation Cost passes to the next generation as a way to progressively discard solutions having non-zero PNS values.

The mutation occurs after the reproduction phase. An individual and then one of its genes are randomly chosen, and that gene is changed using the gene of another randomly selected individual. Then a new offspring population is created, in which, some individuals were mutated. Finally, the selection block classifies non-dominated individuals, i.e., the ones that are associated to non-dominated solutions using equation (22). If the number of the selected individuals, that is, the non-dominated solutions is smaller than the size of the population, then a tournament selection based on the operational costs is used to complete the population. This tournament selection also includes a Tabu list in order to ensure diversity. At the end of this step, the new population will be formed by the non-dominated individuals and the winners of the selection tournaments. This process is repeated until the convergence criterion is achieved or eventually the maximum number of iterations is run.

The improvement block is based on the individual's characteristics, that is, if an individual has an unacceptable PNS, it is improved inserting new equipments selected using a CHA. On the other hand, if this individual displays an appropriate value to PNS, it is improved by eliminating equipments (change in the gene) using Hill Climbing Method. According to this method, an equipment is removed and the new individual is evaluated again. If the resulting PNS value continues appropriate this change is confirmed. If not, the mentioned equipment is included back in the individual.

CHAs are tools that have a low computational effort and that produce acceptable solutions [9], which makes their use interesting in hybridizing algorithms of the TEP problem. Basically, in each iteration these tools build a part of the solution, that is, new equipments are inserted in each iteration in order to progressively reduce or even eliminate PNS. The addition of new equipments occurs according to a preselected sensitivity criterion. In this case it was used the transited power flow, i.e, the addition is conducted in paths that display a larger congestion level.

The Hill Climbing method is a local search approach that starts with a solution and that tries to find better solutions in their neighborhood, through small changes in the current solution. In the present case, this tool checks if a particular equipment is crucial for the performance of that solution, i.e. if equipment is removed, the feasibility of the solution is checked in terms of having or not PNS. If the solution remains feasible, that is if PNS = 0 the elimination of that equipment is confirmed. This technique requires the specification of the maximum number of individuals that will be analyzed (Max_Tries) as well as the maximum number of gene changings that are simulated (MaxFlips).

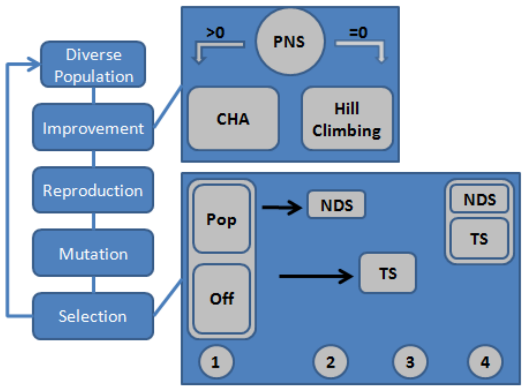

Figure 3: Overview of the application of the NDCCGA to the TEP problem.

Fig. 3 displays an overview of developed algorithm. In the selection block population (Pop) and offspring (Off) leads to the non-dominated solutions (NDS) and the tournament selection (TS) that incorporates the mentioned Tabu list to generate the new population.

It is worth emphasizing that the improvement block was introduced by the authors due to two factors:

i. Genetic algorithms may have a high computational effort, i.e. require a large number of iterations to converge. On the other hand, when considering an improvement block to accelerate the convergence, the population diversity may be compromised because individuals may become local optima. The mentioned Tabu list was used to overcome these problems;

ii. When unfeasible solutions are modified introducing more equipments to regain feasibility, the generation dispatch becomes more flexible, that is, it is more likely to further reduce the level of emissions. On the other hand when removing some equipment the dispatch becomes less flexible and the level of emissions is likely to increase. Obviously, changing the number of equipments in the system also changes the investment cost. These changes are important in the scope of the iterative process detailed before because the investment cost and the level of emissions change eventually turning some solutions non-dominated. In particular, the extreme sides of the Pareto front may gain new solutions because including new equipments will increase the investment cost and conversely removing some equipments will reduce it.

V. Tests and Results

The Non-Dominative CHA-Climbing Genetic Algorithm described in Section IV was applied on the modified IEEE 24 Bus Reliability Test System. The system used in the tests has some differences regarding the test system proposed in [10] as described below:

- Emergency Condition to the maximum allowed flow in a particular branch;
- To ensure the convergence of the AC-OPF, the loads were considered dispatchable as described in [11]. In this approach the loads are modeled as negative real power injection with associated negative costs. This modeling is performed using a negative output generator, ranging from a minimum injection equal to the negative total load to a maximum injection of zero. This means the problem has enough flexibility to reduce the demand if that is required to maintain feasibility. Additionally, if the entire load is not supplied the reactive demand is reduced in the same proportion as a way to keep the power factor of the original load.
- Reactive power sources are located in particular buses, as suggested in [12] and according to Table 1;

TABLE I. VOLTAGE CORRECTION DEVICES

VOLTAGE CORRECTION DEVICES			
DEVICE	BUS	MVAR	CAPABILITY
SYNCH. CONDENSER	3	350	CAPACITIVE
SYNCH. CONDENSER	9	510	CAPACITIVE

- The values of all loads and of the installed capacity of all generators were tripled (real and reactive) in order to turn the network more stressed.

According to Section IV, NDCCGA was used to build the Pareto front integrating solutions that reflect a trade-off between the minimization of Emissions (F1) and Investment Costs (F3). This new tool was used with a population of 1000 individuals, penalty factor for PNS equals to 10^7 €/MW and the cost of dispatchable loads was set at 10^6 €/MW, 1 MW for allowed PNS, the MaxTries equals to 30 and 50 for MaxFlips. The voltage limit on the bars is 5% (0.95 and 1.05 p.u). The iterative process finishes when the solutions in the Pareto Front obtained in two consecutive iterations do not change more than a specified threshold. In the simulations to be detailed below convergence was obtained after running 300 iterations because from that point onwards the changes in the Pareto Front were neglectable.

The developed software converged in about 34 hours, solving 969.148 AC-OPFs, the NDCCGA was implemented in MATLAB, running on an Intel i7, 3.4GHz, 8 GB RAM, hardware platform and the AC-OPFs was solved with interior point solver using MATPOWER tool described in [11].

Figure 3 presents the Pareto front of the TEP problem. Solution 8 has the largest investment cost and the lowest CO2 emissions. On the other hand, solution 1 presents the lowest investment cost and the largest CO2 emissions. The other solutions indicated in Fig.3 are detailed in the Table 2.

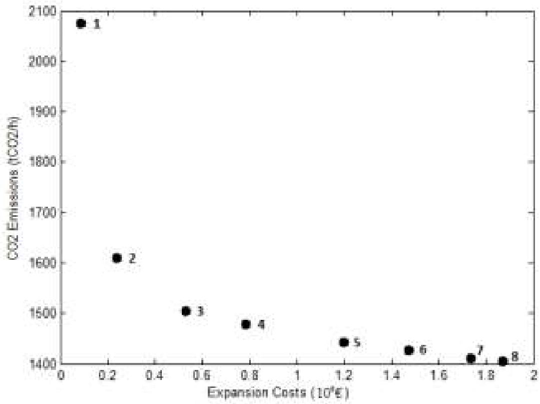

Figure 3: Pareto Front for minimizing Investment costs and CO_2 emissions.

TABLE II. DETAILED SOLUTIONS

Solution	Expansion Planning (path)	Operational costs (€/h)	Emissions (tCO2/h)	Expansion Costs (10^9€)
1	138 kV cable (06-10), 138 kV line (07-08) and 230 kV line (14-16)	$1,7494.10^6$	2075,17	0,086
2	138 kV cable (06-10), 138 kV line (07-08), 230 kV line (11-13), 230 kV line (15-21) and 230 kV line (15-24).	$1,7690.10^6$	1610,27	0,2380
3	138 kV cable (06-10), 138 kV line (07-08), Transformer (10-12), 230 kV line (11-13), 230 kV line (12-23), 230 kV line (15-21), 230 kV line (16-17) and 230 kV line (17-22).	$1,7521.10^6$	1505,36	0,532
4	138 kV cable (06-10), 138 kV line (07-08), Transformer (10-11), (2) 230 kV line (11-13), (2) 230 kV line (12-23), (2) 230 kV line (15-21), 230 kV line (15-24) and 230 kV line (21-22).	$1,7473.10^6$	1479,08	0,784
5	(2) 138 kV cable (01-02), Transformer (03-24), (2) 138 kV line (04-09), (2) 138 kV line (05-10), (2) 138 kV line (07-08), (2) 138 kV line (08-10), (2) Transformer (10-11), Transformer (10-12), 230 kV line (11-14), 230 kV line (13-23), 230 kV line (15-16),230 kV line (16-19), 230 kV line (17-22), (2) 230 kV line (18-21), (2) 230 kV line (19-20), (4) 230 kV line (20-23) and 230 kV line (21-22).	$1,7406.10^6$	1443,09	1,200
6	138 kV line (04-09), 138 kV line (05-10), 138 kV cable (06-10), (2) 138 kV line (07-08), Transformer (10-12), 230 kV line (11-13), (5) 230 kV line (12-23), 230 kV line (14-16), 230 kV line (11-13), (2) 230 kV line (15-21), 230 kV line (15-24), 230 kV line (16-17) and (2) 230 kV line (17-22).	$1,7375.10^6$	1426,45	1,474
7	Transformer (03-24), 138 kV line (04-09), 138 kV line (05-10), 138 kV cable (06-10), (2) 138 kV line (07-08), Transformer (10-12), 230 kV line (11-13), (5) 230 kV line (12-23), 230 kV line (14-16), 230 kV line (11-13), (2) 230 kV line (15-21), 230 kV line (15-24), (2) 230 kV line (16-17), (3) 230 kV line (17-22) and 230 kV line (20-23).	$1,7348.10^6$	1411,81	1,736
8	Transformer (03-24), 138 kV line (04-09), 138 kV line (05-10), 138 kV cable (06-10), (2) 138 kV line (07-08), Transformer (10-12), 230 kV line (11-13), (5) 230 kV line (12-23), 230 kV line (14-16), 230 kV line (11-13), (3) 230 kV line (15-21), 230 kV line (15-24), (2) 230 kV line (16-17), (3) 230 kV line (17-22), (2) 230 kV line (20-23) and (2) 230 kV line (21-22).	$1,7336.10^6$	1405,39	1,870

Therefore, this approach provides the set of solutions among which the TSO will select the one to expand the network according to values obtained for Functions F1, F2 and F3 and also having in mind limits for instance related with the maximum investment cost, GHG emission reduction agreements, etc.

VI. Conclusions

This paper presents a new tool able to deal with multi-objective Transmission Expansion Planning problems. The multi-objective formulation includes the reduction of the CO_2 emissions (given that there is a growing concern because of its impact on global warming) and the minimizing of the investment costs in network equipments.

The Non-Dominative CHA-Climbing Genetic Algorithm has the general blocks of a regular genetic algorithm with the addition of an improvement block and a Tabu list. The improvement is made using Constructive Heuristic Algorithms and Hill Climbing method. Each candidate solution is analyzed using an AC-OPF model that was preferred to DC based versions in view of the existing gap between these two models.

The NDCCGA was applied to the IEEE 24-Bus Reliability Test System modified with the inclusion of two voltage control devices and the network operating conditions were stressed tripling the generation capacities and the loads, which in turn were considered as dispatchable. The tool showed excellent performance providing a number of different expansion plans with different values of CO_2 emissions and investment costs. This enables the decision maker to select the final one in a more informed way.

The main contribution of this paper is the development of NDCCGA tool that provides to the end of its iterative process a tradeoff between investment cost and emissions without the individual and separate minimization, as in other approaches. This process proved to be beneficial since it saves computational effort, which in this case enabled using a more complete AC-OPF model.

VII. Acknowledgements

The first author thanks CAPES Foundation, Ministry of Education of Brazil, for financing this research and Dr. Suzana Menezes de Souza for the several teachings provided in the INESC TEC premises.

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B.0.6 Transmission system planning considering solar distributed generation penetration. (IEEE European Energy Market, 2017)

Transmission System Planning Considering Solar Distributed Generation Penetration

Phillipe Vilaça Gomes[1, 2], João Tomé Saraiva[1, 2]
[1] Faculdade de Engenharia da Universidade do Porto, Porto, Portugal.
[2] INESC TEC, Porto, Portugal.
email: phillipe.gomes@fe.up.pt, jsaraiva@fe.up.pt

Abstract — **In recent years, power systems have been watching important advancements related with Plug-in-Electrical Vehicles (PEVs), Demand Side Management (DSM), Distributed Generation (DG), Microgrid and Smart Grid installations that directly affect distribution networks while impacting indirectly on Transmission studies. These changes will lead to an extra flexibility on the transmission-distribution boundary and to a significant modification of the load patterns, that are an essential input to planning studies. In this scope, this paper describes a multiyear Transmission Expansion Planning (TEP) solved by Evolutionary Particle Swarm Optimization (EPSO) and incorporating the impact of solar DG penetration. The primary substation load profiles and the solar generation profiles are taken into account on the planning problem. The numerical simulations were conducted using the IEEE 24 bus reliability test system in which the planning horizon is 3 years and the load growth is 2.5 % per year. If demand and solar DG peaks are coincident, then the liquid demand seen by the transmission network gets reduced enabling a reduction of investment costs. In the tested cases, these peaks were not coincident so that the optimal expansion plan remains unchanged even though the injected power from DG is large. This stresses the fact that solar DG may not on an isolated way contribute to alleviate the demand seen by transmission networks but should be associated with storage devices or demand side management programs.**

Index Terms — **Multiyear Transmission Expansion Planning, AC – Optimal Power Flow, Solar DG, Evolutionary PSO.**

I. INTRODUCTION

The purpose of a TEP problem is to determine how a transmission system should evolve over time in the most economical way according to the planner's main drivers which, in the case, can correspond to the load growth, the connection of new generation sources or new demand centers, the equipment aging, the improvement of competition between generation companies, changes in export/import patterns between neighbor systems and variations in the supply reliability requirements of customers [1]. Therefore, using a pre-defined list of candidate equipments (transmission lines, cables, transformers, etc.) that can be inserted on the grid, the TEP problem aims at identifying the ones to be built and their commissioning date to attend a pre fixed objective (investment cost, operational cost, GHG emissions, reliability, etc.).

The TEP problem has non-linear and non-convex nature which leads to a huge computational effort. In order to overcome this burden, relaxed models are often used as static approaches or formulations based on the DC power flow. Although their solutions are considered reasonable in the literature, these models don't incorporate a holistic view over the entire planning problem, the reactive power, the branch losses and the voltage limits on the bars are often disregarded, and so its computational effort is lighter. It is then clear that these models don't represent the real world problem so that less realistic solutions can be obtained. In alternative, the original problem should be considered eventually using bioinspired metaheuristics to solve it (instead of traditional mathematical optimization techniques). This kind of tools are able to give optimal or suboptimal solutions taking advantage of patterns recognized in the nature as behaviors of fireflies, bats, ants and swarms for instance.

In order to solve the TEP problem, and apart from other considerations regarding the evolution over time of other input variables (generation, equipments, etc.), we usually consider a scenario for the system demand for each year of the planning horizon. For each of these years and for the transmission assets available in that year an optimal power flow analysis should be done in order to check if the system operates properly, i.e., if there is no congestion on the lines, if Power Not Supplied (PNS) is zero and if the voltage profile is adequate. These demand scenarios can then be addressed using probabilistic or deterministic approaches or considering uncertainties representing vague information provided by the planner for instance under the form of fuzzy concepts. Regarding deterministic approaches, it is typically considered the forecasted annual peak demand as the demand scenario that the system must supply in a secure and reliable way.

The advent of changes namely in distribution networks related with the increasing presence of DG, the development of micro and smart grids and the increasing number of PEV's must also be incorporated in long-term expansion planning methodologies in view of their impact on the network depending on regional incentive policies. In this paper, we

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considered a deterministic load scenario taking into account an increased penetration of solar DG on the IEEE 24 bus RTS in order to investigate how the deployment of this type of DG impacts the definition of the transmission expansion plans. The investigation of this impact can therefore be considered as the main contribution of this paper.

Regarding the structure of the paper, following this Introduction, Section II reviews some concepts related with distributed generation, Sections III presents the mathematical formulation of the dynamic TEP problem and Section IV details the main blocks of the EPSO algorithm. Finally, Section V addresses the methodology used in this paper. Section VI presents the simulation results and Section VII draws the main conclusions of this research.

II. Distributed Generation

Distributed generation is usually as associated to small generation units connected to the power grid either on the customer side or to the distribution network [2]. The size of a typical DG unit ranges from 1 kW to 10 or 20 MW but in some cases, as for large wind parks or solar PV stations, it can reach 100 or 200 MW. Besides, regarding to its primary source, DG can be classified as renewable (solar, wind, hydro) or nonrenewable (internal combustion engine) energy stations.

The exploitation of energy generation from renewable sources has been increasing in several countries, in most cases induced by regulatory incentives for small distributed generation such as Feed-in Tariffs and Net Metering schemes. These incentives are justified by the potential benefits that the deployment of these distributed sources can bring to entire system and to the society as a whole. According to [3] these advantages are related with the possible postponement of expansion investments in distribution and transmission systems, the reduction of the environmental impact, the reduction of the network loading levels, the reduction of losses and the diversification of energy sources.

Although the solar DG penetration is still low in most countries, the global incident solar radiation can reach large values ranging from 900 to 1250 kWh/m² throughout the year in Germany, 900-1650kWh/m² in France, 1200-1850 kWh/m² in Spain and 4200-6700 kWh/m² in Brazil. Therefore, several studies investigate the barriers to DG penetration [4] as well as its impact on the grids [5].

In TEP problems DG is usually modeled as a negative real load, that is, the DG reduces locally the real load on a primary substation. Fig. 1 shows this behavior for a bus over one day (24 hours) on the test system used in this paper. The new demand that will be used to carry out the expansion planning studies takes into account the solar DG penetration. In this example, solar generation starts at 6 am and ends at 6 pm and has a generation peak at 12:00. It should be stressed that the expansion study should continue to be done in a way to ensure the safe operation during the peak demand (19:00), and this drive is not changed while considering the injection of electricity from PV sources on the grid nodes.

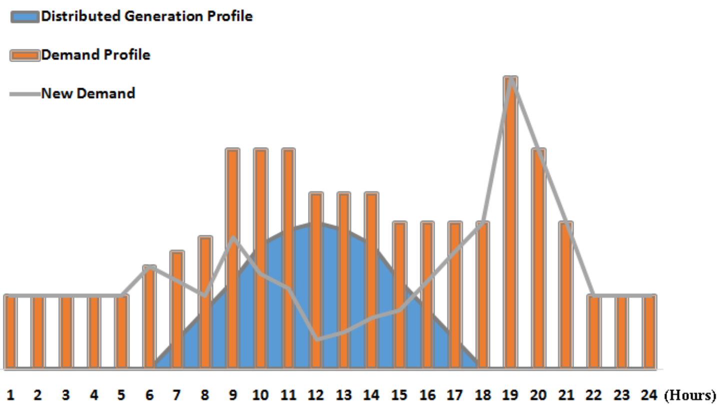

Figure 1. Illustration of the impact of PV generation of the demand profile along one day.

III. TEP Mathematical Formulation

The mathematical formulation adopted in this paper for the TEP problem takes into account the investment cost ($C_{inv,p}$) and a penalization term (β) for Power Not Supplied (PNS). This means that one possible expansion plan is characterized by the investment cost associated to the insertion of new equipments on the grid on specific years and by the expected PNS in each year of the horizon when the annual peak load is applied on the system. A solution is considered feasible when it is able to ensure a safe operation of the system over the planning horizon, that is, it displays zero PNS in every year of the horizon. Furthermore, the formulation includes physical constraints related with the branches and generator capacity limits, financial limitations related with the capital available in each year or along the entire planning horizon and quality of supply constraints associated to reliability indices. According to these ideas, the associated TEP problem can be formulated by (1) to (4).

$$\text{Minimize } \sum_{p=1}^{np} \kappa_p . C_{inv,p} + \beta . PNS \tag{1}$$

Subject to:

$$\text{Physical Constraints} \tag{2}$$
$$\text{Financial Constraints} \tag{3}$$
$$\text{Quality of service Constraints} \tag{4}$$

In this formulation κ_p is the present-worth value coefficient given by (5), d is the discount rate and p is the index associated to each period in the planning horizon.

$$\kappa_p = \frac{1}{(1+d)^p} \tag{5}$$

Although the AC power flow (AC-OPF) requires a larger computational burden, this is the most adequate model to deal with TEP problems because it considers the reactive power, the losses and the bus voltage limits. Therefore, we used an AC-OPF based model in order to compute the PNS when the system supplies the annual peak demand for each planning year and incorporating the new equipments included in the expansion plan. Given the fact that the AC-OPF problem has to be solved a large number of times, associated to the years in the planning horizon and with the trial expansion plans to test, we used the MATPOWER tool [6] to assist the solution of the mentioned AC-OPF problem.

The AC-OPF used in this paper is formulated by (6) to (14): For a given trial expansion plan being tested, this problem is solved for each year in the planning horizon considering in each year the new equipments that are included in that solution until the year under analysis.

$$\text{Min PNS} \tag{6}$$

subject to

$$P(V,\theta,n) - P_G + P_D = 0 \tag{7}$$
$$Q(V,\theta,n) - Q_G + Q_D = 0 \tag{8}$$
$$P_{G\min} \le P_G \le P_{G\max} \tag{9}$$
$$Q_{G\min} \le Q_G \le Q_{G\max} \tag{10}$$
$$V_{\min} \le V \le V_{\max} \tag{11}$$
$$(N+\overset{o}{N})S^{from} \le (N+\overset{o}{N})S_{\max} \tag{12}$$
$$(N+\overset{o}{N})S^{to} \le (N+\overset{o}{N})S_{\max} \tag{13}$$
$$0 \le n \le n_{\max} \tag{14}$$

In this formulation, the objective function (6) corresponds to the minimization of PNS, P_G and Q_G are the active and reactive power generation, P_D and Q_D are the active and reactive power demand, V is the voltage magnitude, S_{ij}^{from} and S_{ij}^{to} are the apparent flows in branch ij, N and $\overset{o}{N}$ are diagonal matrixes containing the inserted equipments and the base topology equipments.

The solution having the lowest value for Eq. (1) is considered the optimal solution and will be analyzed considering issues as the operation costs, reliability, losses and environmental impact.

IV. EPSO Algorithm

EPSO is a powerful tool that combines concepts of evolutionary computation and multi agent population taking advantage of the standard blocks that are typical in Genetic Algorithm and in Particle Swarm Optimization. This tool is able to combine the best features of these two groups of techniques and therefore has excellent performance in solving complex problems such as the one addressed in this paper.

This algorithm is based on the evolution of a set of particles, each of them representing solutions for the problem. Along the evolution process the particles evolve according to a fitness function and continue to improve in each iteration until the process reaches a pre-established stopping criterium, and the best solution of the last population is provided to the user. Fig. 2 details the main blocks of the EPSO algorithm that will also be described in the next paragraphs.

Figure 2. Main blocks of the EPSO Algorithm.

The initial population is created randomly and the developed approach uses a Tabu List to prevent repeating the same particle in the population, that is, to increase the diversity of the particles in the initial population. In the replication block each population is cloned r times in order to create new populations that will be mutated in the next block. In the mutation block the weights and the best particle found until now (gbest) for all the populations are mutated using (15) and (16) in which the symbol * denotes the mutation operator. This process increases the diversity of the individuals under analysis.

$$\overset{*}{w}_{ij}^{it+1} = 0,5 + rand() - \frac{1}{1+\exp(-\overset{*}{w}_{ij}^{it})} \tag{15}$$

$$\overset{*}{gbest} = gbest + round(2.\overset{*}{w}_{i4}^{it+1} - 1) \tag{16}$$

Therefore, new populations (offsprings) are created in the recombination block based on the PSO movement rule. According to (17) the position of a particle i in iteration it+1 is the result of its position in iteration it plus the velocity vector given by (18). This procedure is repeated for all particles in the cloned populations.

$$x_i^{it+1} = x_i^{it} + v_i^{it+1} \tag{17}$$

$$v_i^{it+1} = \overset{*}{w}_{i1}^{it+1}.v_i^{it} + \overset{*}{w}_{i2}^{it+1}.(pbest_i - x_i^{it}) + \overset{*}{w}_{i3}^{it+1}.(gbest - x_i^{it}).P \tag{18}$$

The first term in (18) represents the inertia of the particle, the second term represents its individual knowledge and the last term represents the collective knowledge of the swarm. P is the communication factor described in [7]. It typically takes values 0 or 1 so that if 0 is used for a position of the particle vector then the collective knowledge is not passed to this particle in the next iteration. The evaluation block checks if a candidate plan ensures a safe operation (without PNS) and so its load shedding cost is zero. Otherwise the PNS is multiplied by a penalty factor (in $/MW). Once this step is finished, all the particles are characterized by their investment and expected load shedding costs. In the selection block a tournament selection is performed to build the new population having the same size of the initial one. The iterative process continues until the best solution remains unchanged along a pre-defined number of iterations. In the selection block it was also used a Tabu List in order to ensure the diversity of the new population. This list checks if one solution is already in the population. If so it modifies this solution selecting randomly one investment in this solution and postponing it by moving it one year ahead.

TEP problems have integer nature which leads to the phenomenon of combinatorial explosion of investment alternative plans. This characteristic typically leads to a high computational effort to identify good quality plans. In order to tackle this problem, the described EPSO algorithm was implemented using parallel computing.

V. METHODOLOGY

In this paper the penetration of solar DG was organized in 4 scenarios: 0%, 10%, 15% and 20% of the annual peak demand connected to each bus. After the optimization process carried out by the EPSO algorithm is done (considering the new peak demand for each scenario), the DG impact is analyzed considering four items: reliability, economic aspects, losses and environmental aspects. The probabilistic index Expected Energy Not Supplied (EENS) is used to measure the system reliability. EENS reflects not only the base topology and physical limits of the system under analysis but it also incorporates uncertainties associated with the non-ideal behavior of system components. In order to estimate the EENS it is not enough to sample components out of service. In fact it is necessary to sample operation and repair times of the components in order to access the duration of each state which justifies using a chronological Monte Carlo as detailed in [8].

Regarding the economic analysis, four load blocks representing one day of each season of the year are used in order to estimate the operation costs. Each primary substation (represented by the buses of the system) have their own load profile and these values can be assessed in [9] taking into account the Monday of the 2nd week for the Winter, the Saturday of the 13th week for the Spring, the Friday of the 24th week for the Summer and the Sunday of the 41st week for Autumn. The methodology discussed in this paper is illustrated in Fig. 3.

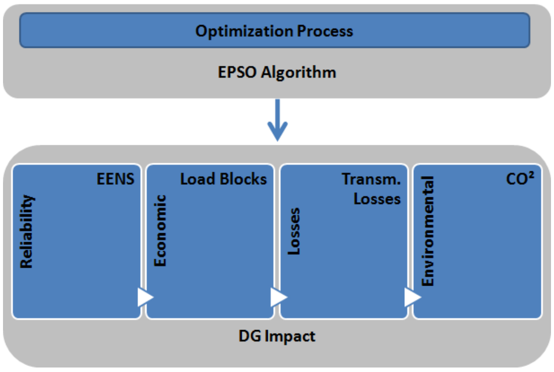

Figure 3. Methodology for DG impact on TEP

As an example, Fig. 4 represents the new load profile for each season of the primary substation connected to bus 1 assuming a 10% DG penetration (as suggested by Fig. 1). In this paper, the maximum solar generation (solar peak at 12:00) for each bar is assumed to be proportional to its annual peak load. As an example, Fig. 5 presents the DG generation in MW in each bus for the three penetration levels that were considered, 10%, 15% and 20%. As a whole, the 10% level of penetration is associated to an installed capacity of 570 MW, 15% is associated to 855 MW and 20% to 1140 MW for the annual peak demand of 5700 MW considered in the first year.

VI. RESULTS

This section presents the results obtained using the proposed TEP approach when applied to a modified version of the IEEE RTS 24 bus system [9]. The system that was used has some differences regarding the original one, as described below:

i. the loads are modeled as negative real power injections with associated negative costs as described in [10];
ii. the values of all the loads were duplicated and the installed capacity of all generators were tripled (real and reactive) in order to turn the transmission network more stressed;
iii. the modified system has 9 hydro generators that have initial maximum capacity of 2880 MW (28,2% of the total capacity of the system) as follows:
    - 6 hydro generators of 150 MW in bus 22;
    - 1 hydro generator of 1050 MW in bus 23;
    - 1 hydro generator of 465 MW in bus 15;
    - 1 hydro generator of 465 MW in bus 16;

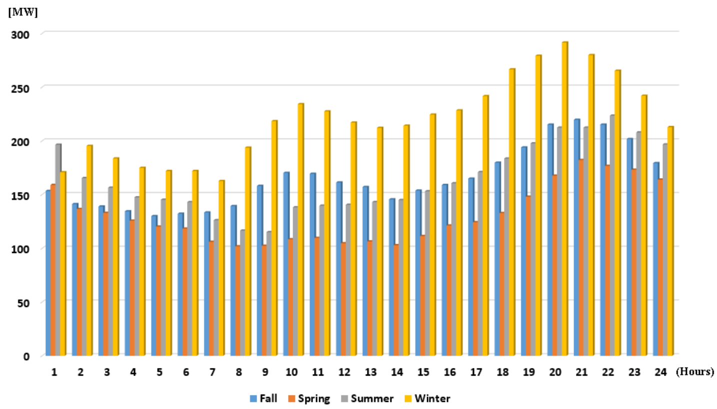

Figure 4. New load profile for the bus 1 (with 10% DG penetration).

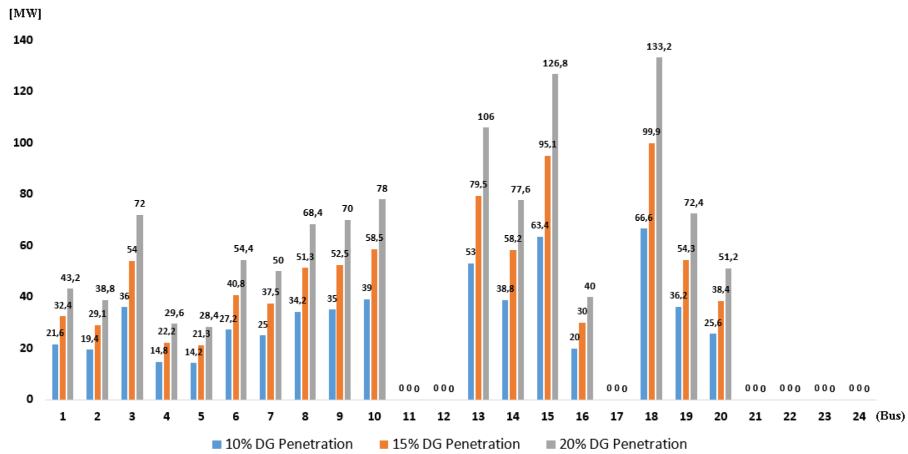

Figure 5. DG penetration by bus and scenario at 12 am (Peak of solar generation).

The initial peak demand is 5700 MW and the total generation capacity is 10215 MW. Regarding the CO_2 emissions, we use data from [11]. The load growth was set at 2,5% per year and the discount rate was set at 5% per year, the number of particles in each population of the EPSO algorithm was set at 50, the planning horizon is 3 years and the PNS penalization cost was set at 10^9 \$/MW. The EPSO algorithm stops after running 50 iterations with the same best solution. The simulations were run in MATLAB with an Intel i7, 3.4GHz, 8 GB RAM.

As the annual peak load for this system occurs after 6 pm, the solar distributed generation has no impact in decreasing it since no associated storage devices are being considered. Additionally, the optimization process takes into account only the minimization of the investment cost for new equipments on the grid while ensuring that the annual peak demand is supplied. Therefore, for the considered cases (solar DG penetration of 0%, 10%, 15% and 20%) the annual peak demand is the same which means that the optimal expansion plan identified by the EPSO algorithm remains unchanged. This plan was obtained running 112 iterations in 42 minutes. The evolution of the solution is shown in Fig. 6 below and for each analyzed case Table I provides the values of the indices used to analyze the obtained expansion plan considering the DG penetrations that were tested.

The best solution found by EPSO algorithm corresponds to the installation of:

- Year 1 - a transformer between bus 3 and 24, one 138 kV cable connecting bus 6 to 10, one 138 kV line connecting buses 7 to 8;
- Year 2 - one 138 kV line connecting buses 1 to 5 in the second year.

These equipments allow the system to gain flexibility enough to accommodate the demand in Period 3 so that no new equipment is required in this period.

Table 1: Comparison of the results for the 4 DG penetration scenarios.

Cases	DG penetration	Inv. Cost (10^6 US$)	Op. Cost (10^6 US$)	EENS (MWh/year)	Trans. Losses (MW)	CO_2 Emissions (t CO_2)
1	0 %	98.05	47.60	38295,98	14808.07	62131.47
2	10 %	98.05	39.08	29563,18	14072.61	51495.52
3	15 %	98.05	35.43	27126,98	13690.19	47620.69
4	20 %	98.05	32.47	25739,72	13372.85	43649.91

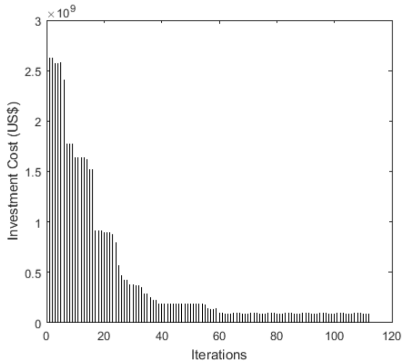

Figure 6. Evolution of the best particle of the EPSO Algorithm.

VII. Conclusions

This paper describes a multiyear transmission expansion planning considering solar distributed generation penetration. The planning problem is conducted considering the investment cost and a penalization for Power Not Supplied over the planning horizon. On the other hand, Evolutionary Particle Swarm Optimization is used to solve the optimization problem via a parallel computing approach as a way to reduce the computation time. The develop approach models solar distributed generation as negative loads in each bar considering the solar penetration proportional to the demand.

The main motivation to develop this TEP approach comes from the need to consider in the transmission planning task the new load behavior present in the transmission-distribution boundary. The new load profiles are becoming increasingly affected by Plug-in-Electrical Vehicles, Demand Side Management Programs, Distributed Generation (DG) penetration and Microgrid and Smart Grid installations. Although affecting in a direct way distribution networks, these aspects impact indirectly on the transmission grids.

The results presented in Table I indicate that the penetration of solar distributed power generation can provide a better and safer operation for the system while reducing the operation costs, the transmission losses and the CO_2 emission level while contributing to diversify the generation mix. In this case the peak of injected solar DG is not coincident with the annual demand peak period which means that the annual peak demand seen by the transmission network remains unchanged. As a result, even if the injected solar DG is increased to 20% of the peak demand in each bus, the optimal expansion plan remains unchanged. This suggests that solar DG is not able in an isolated way to reduce the liquid demand seen by transmission networks and thus contribute to postpone transmission investments and reduce the corresponding cost. Therefore, as main conclusion of this paper, solar DG should be associated to storage devices or demand side management programs should be implemented in order to reduce the investment effort in transmission networks.

Acknowledgment

The first author thanks CAPES Foundation, Ministry of Education of Brazil, for financing this research.

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B.0.7 Multiyear transmission expansion planning under hydrological uncertainty. (IEEE Powertech, 2017)

Multiyear Transmission Expansion Planning Under Hydrological Uncertainty

P. Vilaça Gomes, *Student Member, IEEE* and J. T. Saraiva, *Member, IEEE*
INESCTEC and Faculty of Engineering of University of Porto, Portugal
Rua Dr. Roberto Frias 4200-465 Porto Portugal
phillipe.gomes@fe.up.pt, jsaraiva@fe.up.pt

***Abstract*— Hydrothermal systems should be characterized by a transmission-intensive nature in order to deal with climatic phenomena which, for example, can determine dry conditions in one region while there are large rainfalls in another one. Thus, the grid must be robust to deal with the different export/import patterns among regions and accommodate several economic dispatches. This paper describes a multiyear probabilistic Transmission Expansion Planning, TEP, model that uses Evolutionary Particle Swarm Optimization (EPSO) to deal with the uncertainties present in hydrothermal systems. The numerical simulations were conducted using the IEEE 24 bus reliability test system in which the planning horizon is 10 years and the load growth is 2,5% per year. The results highlight the importance of adopting expansion strategies to reduce the risk and consider the inflow variations in this type of systems.**

***Index Terms*-- Transmission Expansion Planning, Probabilistic Approach, Uncertainties, Evolutionary Particle Swarm Optimization.**

I. INTRODUCTION

The restructuring of the electricity sector which occurred especially in the last two decades led to the separation of the generation, transmission, distribution and retailing of electricity activities in several countries [1]. In this context, the activities of generation and retailing are now provided in free competition while network services, namely transmission, are provided in term of regulated monopolies. This separation introduces a higher degree of complexity in long-term planning. To further complicate the planning activities, hydrothermal systems should have a transmission-intensive nature in order to deal with the climatic phenomena which, for example, can determine dry conditions in one region while there are increasing rainfalls in another one. Thus, the grid must be robust enough to deal with the different export/import patterns among regions and be able to accommodate several economic dispatches [2]. These reasons combined with the importance of the electric sector in the economy and sovereignty of a country turn the Transmission Expansion Planning (TEP) one of the biggest challenges faced by researchers in the power systems area.

TEP is a problem that has non-linear and non-convex characteristics. It is also characterized by a combinatorial explosion phenomenon, that is, a huge number of expansion possibilities which leads to an enormous computational burden. These aforementioned difficulties lead to a diffusion of relaxed models such TEP approaches based on DC Model [3]. This model does not consider the reactive power, the branch losses and the voltage limits on the bars, and so its computational effort is lighter. However, it does not represent the real behavior of an AC grid and therefore can lead to solutions that corresponds to undervalued investments while also leading to serious violations of network constraints in their solutions when are checked against pure AC TEP models as reported in [4], [5]. In order to overcome these problems, the TEP problem was solved using the AC model in [6], [7].

Apart from DC based models, the TEP literature also includes several models in which the holistic planning view is discarded (static models) in order to reduce the computational burden. In these static approaches each planning period is analysed at a time and an equipment (transmission lines, transformer, cables) is selected in a given period and it is considered as available on the next one [8]. However, the multiyear (or dynamic) nature is very important in TEP problems once it preserves the holistic view on the planning exercise. In dynamic approaches the entire planning horizon is taken at the same run [9], which is essential to adequately select investment alternatives in long term problems.

This paper describes a probabilistic multiyear TEP model that uses EPSO to address its particular characteristics. It also considers different hydro inflows as well as a risk index to measure the annual deficit of the system in supplying the demand. The main contributions of this paper are as follows:

i) TEP is performed considering several hydro shares generation scenarios in a multiyear approach and it incorporates the AC Optimal Power Flow (AC-OPF) to adequately model the operation of the network. Therefore, this TEP approach is more realistic since it uses a probabilistic approach, it preserves the holistic planning view and uses the AC model that truly represents the network behavior;
ii) The EPSO algorithm is implemented using the concept of parallel computing. Due the huge computational burden required to solve the TEP problem considering several hydro scenarios, this approach can save time and enable analyzing realistic systems in the future.

CAPES Foundation, Ministry of Education of Brazil.

Regarding the structure of the paper, following this Introduction, Section II addresses the uncertainties intrinsic to hydrothermal systems and Section III describes the mathematical formulation of the dynamic TEP problem. Then, Section IV details the main blocks of the EPSO algorithm, Section V presents the simulation results and finally Section VI draws the main conclusions of this research.

II. Hydrological Uncertainties

Hydrothermal systems must have a strong transmission grid because transferring huge energy blocks from wetter to drier regions is frequently required. Therefore, when the TEP problem is solved it must consider several and different dispatch patterns in order to reduce the risk of having Power Not Supplied (PNS). Thus, hydrological uncertainties must be taken into account when addressing the TEP problem.

In this paper, the hydrological uncertainties were addressed through scenarios over the planning horizon. The hydrological scenarios are generated considering the initial hydro share (ε_0), the number of scenarios (*Nscen*) and the maximum annual variation for the hydro shares ($\Delta\varepsilon_M$). The hydro shares for a scenario in period p (ε_p) are calculated using (1) and this process is illustrated in Fig. 1 considering 20 hydro inflows.

$$\varepsilon_p = \varepsilon_{p-1} + randb(-\Delta\varepsilon_M : +\Delta\varepsilon_M) \quad (1)$$

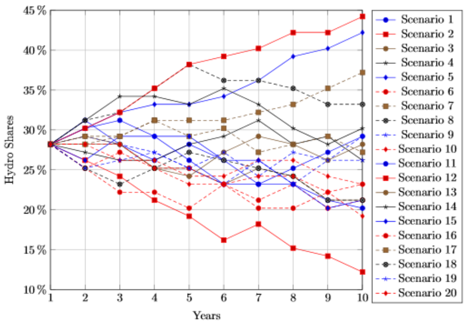

Figure 1. Hydro share generation scenarios.

Besides the hydro shares scenarios for the annual system mix, it is also important to consider different scenarios for the hydro generators of the system, that is, the participation factor for each hydro generator as illustrated in Fig. 2 for a power system having hydro generators in buses 15, 16, 22 and 23.

According to Fig. 2, considering scenario 1 for instance, the generators in buses 15, 16, 22 and 23 contribute to the total hydro share in that scenario and along the planning horizon according to the following percentages: 3.48%, 6.83%, 20.38% and 69.31%.

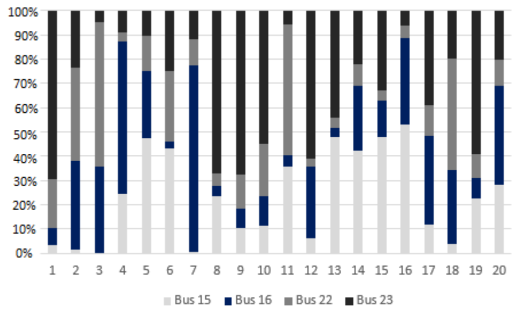

Figure 2. Bus participation factor for each generation scenario.

Apart from that, the minimum and maximum limits of the reservoirs must be respected and so the model ensures that the hydro generation capacity lies between zero and 1,5 times the initial capacity. This means that if in a scenario and in a bus the available hydro share and the bus participation factor indicate that the reservoir level is outside these limits, then that level is set at the violated extreme value.

Additionally, the developed approach incorporates an annual deficit risk index of the system (χ) not being able to supply the demand. This index is defined as the percentage of scenarios for which a particular expansion plan is not able to supply the demand, that is, it originates power not supplied. In order to be considered as a feasible solution for the TEP problem, any expansion plan should have a value of this risk index below a specified threshold.

III. TEP Mathematical Formulation

The mathematical formulation discussed in this paper takes into account the investment ($C_{inv,p}$) and the expected load-shedding costs ($C_{ELS,p}$). Furthermore, the physical (branches and generator capacity limits), financial (capital available in the period) and quality of supply constraints (reliability indices) are also considered. The associated TEP problem can be formulated by (2) to (5).

$$\text{Minimize } \sum_{p=1}^{np} \kappa_p.(C_{inv,p} + C_{ELS,p}) \quad (2)$$

Subject to:

Physical Constraints (3)
Financial Constraints (4)
Quality of service Constraints (5)

In this formulation κ_p is the present-worth value coefficient given by (6) and d is the discount rate.

$$\kappa_p = \frac{1}{(1+d)^p} \quad (6)$$

In order to compute the $C_{ELS,p}$ for the topology of the system in each planning year considering also the new equipments included in the expansion plan under analysis we used an AC-OPF based model. This model represents the true behavior of the AC network once it considers the reactive power, the voltage limits on the bars and the branch losses. In this paper we used the MATPOWER tool [10] to assist the solution of the mentioned AC-OPF problem in a very efficient way because this routine is called a large number of times.

The AC-OPF used in this paper is formulated by (7) to (15) and it considers the new equipments on the grid proposed by the expansion planning in study. In this problem, we used the operation cost as the generator dispatch merit order.

$$\text{Min } C_{OP} = \sum \alpha_{i1}.P_i^2 + \alpha_{i2}.P_i + \alpha_{i3} \tag{7}$$

subject to

$$P(V,\theta,n) - P_G + P_D = 0 \tag{8}$$

$$Q(V,\theta,n) - Q_G + Q_D = 0 \tag{9}$$

$$P_{G\min} \le P_G \le P_{G\max} \tag{10}$$

$$Q_{G\min} \le Q_G \le Q_{G\max} \tag{11}$$

$$V_{\min} \le V \le V_{\max} \tag{12}$$

$$(N + \overset{o}{N})S^{from} \le (N + \overset{o}{N})S_{\max} \tag{13}$$

$$(N + \overset{o}{N})S^{to} \le (N + \overset{o}{N})S_{\max} \tag{14}$$

$$0 \le n \le n_{\max} \tag{15}$$

In this formulation $P(V,\theta,n)$ and $Q(V,\theta,n)$ are calculated by (16) and (17), and the bus conductance G and susceptance B are given by (18) and (19).

$$P(V,\theta,n) = V_i \sum V_j [G_{ij}(n).\cos\theta_{ij} + B_{ij}(n).\sin\theta_{ij}] \tag{16}$$

$$Q(V,\theta,n) = V_i \sum V_j [G_{ij}(n).\sin\theta_{ij} - B_{ij}(n).\cos\theta_{ij}] \tag{17}$$

$$G = \left\{ \begin{array}{l} G_{ij}(n) = -(n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \\ G_{ii}(n) = \sum_{j\in\Omega_i} (n_{ij}.g_{ij} + \overset{o}{n}_{ij}.\overset{o}{g}_{ij}) \end{array} \right\} \tag{18}$$

$$B = \left\{ \begin{array}{l} B_{ij}(n) = -(n_{ij}.b_{ij} + \overset{o}{n}_{ij}.\overset{o}{b}_{ij}) \\ B_{ii}(n) = b_{ij}^{sh} + \sum_{j\in\Omega_i} [n_{ij}(b_{ij} + b_{ij}^{sh}) + \overset{o}{n}_{ij}(\overset{o}{b}_{ij} + \overset{o}{b}_{ij}^{sh})] \end{array} \right\} \tag{19}$$

The apparent flows S_{ij}^{from} and S_{ij}^{to} in branch ij are calculated by (20) and (21) where P_{ij}^{from}, Q_{ij}^{from}, P_{ij}^{to} and Q_{ij}^{to} are given by (22) to (25).

$$S_{ij}^{from} = \sqrt{(P_{ij}^{from})^2 + (Q_{ij}^{from})^2} \tag{20}$$

$$S_{ij}^{to} = \sqrt{(P_{ij}^{to})^2 + (Q_{ij}^{to})^2} \tag{21}$$

$$P_{ij}^{from} = V_i^2.g_{ij} - V_i.V_j(g_{ij}.\cos\theta_{ij} + b_{ij}.\sin\theta_{ij}) \tag{22}$$

$$Q_{ij}^{from} = -V_i^2.(b_{ij}^{sh} + b_{ij}) - V_i.V_j(g_{ij}.\sin\theta_{ij} - b_{ij}.\cos\theta_{ij}) \tag{23}$$

$$P_{ij}^{to} = V_j^2.g_{ij} - V_i.V_j(g_{ij}.\cos\theta_{ij} - b_{ij}.\sin\theta_{ij}) \tag{24}$$

$$Q_{ij}^{to} = -V_j^2.(b_{ij}^{sh} + b_{ij}) + V_i.V_j(g_{ij}.\sin\theta_{ij} + b_{ij}.\cos\theta_{ij}) \tag{25}$$

In this formulation, the objective function (2) corresponds to the operation cost of a hydrothermal system where α_{i1}, α_{i2} and α_{i3} are coefficients of the quadratic generator cost functions of each hydro/thermal generation unit *i* dispatching a real power P_i (hydro generator have null coefficients). P_G is the real power generation, Q_G is the reactive power generation, P_D is the real power demand, Q_D is the reactive power demand, V is the voltage magnitude, S_{ij}^{from} and S_{ij}^{to} are the branch apparent flows in terminals, and g_{ij} and b_{ij} are the conductance and the susceptance of branch i-j.

IV. Evolutionary Particle Swarm Optimization

EPSO is a powerful tool that combines concepts of evolutionary computation and multi agent population taking advantage of the standard blocks that are typical in Genetic Algorithms and Particle Swarm Optimization. This tool is able to combine the best features of these two groups of techniques and so it typically shows an excellent performance in solving complex problems such as the one addressed in this paper.

The EPSO algorithm is based on the evolution of a set of particles, each of them representing possible solutions for the problem. Along the process the particles evolve according to a fitness function and continue to improve in each iteration until the process reaches a pre-established stopping criterium. At that point, the best solution of the last population is provided to the user. Fig. 3 details the main blocks of the EPSO algorithm that will also be described in the next paragraphs.

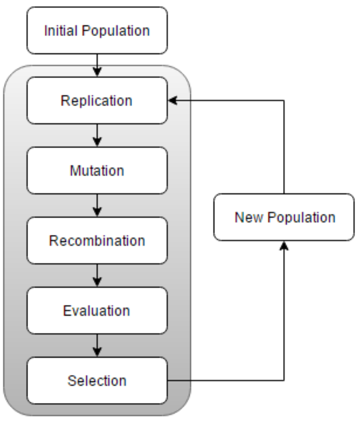

Figure 3. Main blocks of the EPSO Algorithm.

Initial Population

The initial population is created randomly and the developed approach uses a tabu list to prevent repeating the same particle in the population, that is, to increase the diversity of the particles in the initial population.

Replication

Each population is cloned r times in order to create new populations to be mutated in the next block.

Mutation

The weights and the best particle found until now (gbest) for the populations are mutated using (26) and (27) in which the symbol * denotes the mutation operator. This process increases the diversity of the individuals under analysis.

$$\overset{*}{w}_{ij}^{it+1} = 0,5 + rand() - \frac{1}{1+\exp(-\overset{*}{w}_{ij}^{it})} \quad (26)$$

$$\overset{*}{gbest} = gbest + round(2.\overset{*}{w}_{i4}^{it+1} - 1) \quad (27)$$

Recombination

New populations (offsprings) are created based on the PSO movement rule. According to (28) the position of a particle i in iteration it+1 is the result of its position in iteration i plus the velocity vector given by (29). This procedure is repeated for all particles in the cloned population.

$$x_i^{it+1} = x_i^{it} + v_i^{it+1} \quad (28)$$

$$v_i^{it+1} = \overset{*}{w}_{i1}^{it+1}.v_i^{it} + \overset{*}{w}_{i2}^{it+1}.(pbest_i - x_i^{it}) + \overset{*}{w}_{i3}^{it+1}.(gbest - x_i^{it}).P \quad (29)$$

The first term in (29) represents the inertia of the particle, the second term represents its individual knowledge and the last term represents the collective knowledge of the swarm. P is the communication factor described in [11]. It typically takes values 0 or 1 so that if 0 is used for a position of the particle vector then the collective knowledge is not passed to this particle in the next iteration.

Evaluation

The investment and the expected load shedding costs are calculated for all scenarios. If a candidate plan can ensure a safe operation (without PNS) respecting the annual deficit risk of the system, then the load shedding cost is zero, otherwise the average PNS is calculated and multiplied by a penalty factor (in $/MW). The evaluation flowchart for this procedure is shown in Fig. 4.

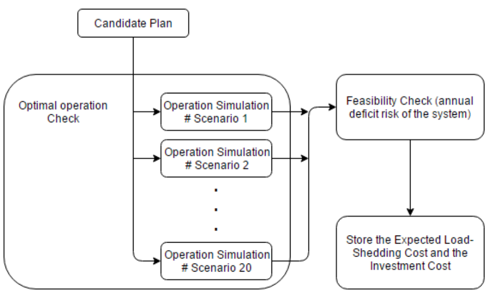

Figure 4. EPSO evaluation block.

Selection

After all the particles are characterized by their investment and expected load shedding costs, a tournament selection is done to build the new population having the same size of the initial one. The iterative process continues until best solution remains unchanged along a pre-defined number of iterations.

In a population with *ps* individuals or particles and considering r clones, *Nsc* hydrologic scenarios and *np* years of planning horizon then the AC-OPF problem is run r x *ps* x *Nsc* x *np* times in iteration. These calculations require a huge computational burden and that was the motivation to implement the EPSO algorithm using parallel computing.

V. Simulation Results

This section presents the results obtained by the proposed TEP approach when applied to a modified version of the IEEE RTS 24 bus system [12]. The used system has some differences regarding the original, as described below:

i. the loads are modeled as negative real power injections with associated negative costs as described in [12]. This modeling is done using negative output generators, ranging from a minimum injection equal to the negative total load to a maximum injection of zero. This means that the AC OPF problem has enough flexibility to reduce the demand if that is required to maintain feasibility. Additionally, if a particular nodal real load is not entirely supplied then the reactive demand is also reduced in the same proportion to keep the power factor of the original load unchanged;
ii. the values of all loads were duplicated and the installed capacity of all generators were tripled (real and reactive) regarding the values in [12] in order to turn the transmission network more stressed;
iii. the modified system has 9 hydro generators that have initial maximum capacity of 2880 MW (28,2% of the total capacity of the system) as follows:
    - 6 hydro generators of 150 MW in bus 22;
    - 1 hydro generator of 1050 MW in bus 23;
    - 1 hydro generator of 465 MW in bus 15;
    - 1 hydro generator of 465 MW in bus 16;

The load growth was set at 2,5% per year and the peak forecasted demand is shown in Table 1. When solving the TEP problem, we also admitted that all transmission equipments in the initial topology could be considered for expansion in terms of installing in parallel a maximum of 2 additional equipments equal to each existing one.

In the performed simulations we used 30 particles in the swarm (ps=30), 20 hydrological scenarios (Nsc=20) as illustrated in Fig. 1 and Fig. 2, 10 years of planning horizon, an annual deficit risk of the system of 5%, which means that an expansion solution is considered as feasible when it ensures a safe operation (without PNS) in at least 95% of the scenarios that is in 19 scenarios out of the 20 analysed scenarios.

TABLE I
Peak demand forecast used along the planning horizon for the modified IEEE RTS 24 bus system.

Year	1	2	3	4	5	6	7	8	9	10
Peak Load (MW)	5700,00	5842,5	5988,56	6138,27	6291,73	6449,02	6610,25	6775,51	6944,89	7118,52

On the other hand, the PNS cost was set at 10^9 \$/MW, and a maximum annual variation for hydro shares equal to 3%. Using these parameters and input data, the process converges in 138 iterations in about 22 hours. Fig. 5 shows the behavior of the best solution in the swarm over the iterative process.

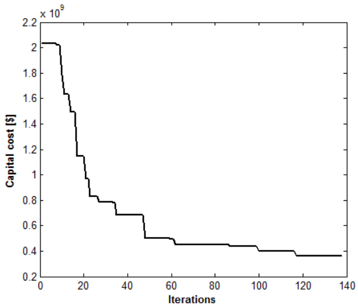

Figure 5. Evolution of the best particle.

Regarding the best solution found over the 10-year planning horizon, the following equipments will be commissioned:

- Year 1 - 138 kV line connecting the buses 1 to 3, 2 to 6 and 8 to 10, one 138 kV cable connecting bus 6 to 10, one 230 kV line connecting buses 12 to 13 and 14 to 16, and one transformer between buses 3 and 24;
- Year 7 - one 138 kV line connecting buses 7 to 8;
- Year 10 - one transformer between buses 9 and 12.

This solution ensures a safe operation in all scenarios except in scenario 16 where this topology does not guarantee the supply of 2 MW. However, the solution is considered feasible as it meets 19 hydrological scenarios thus respecting the annual deficit risk of the system of being below 5%.

Still on the above solution, it is important to notice that most of the equipment is commissioned in the first period because the network is very stressed in the beginning of the planning horison The new equipment gives the system enough flexibility to operate safely until the seventh year. The investment cost for this solution is 0.36 .10^9 \$.

In order to check the quality of the solution obtained using the developed probabilistic approach, the planning exercise was also done in a deterministic way considering that the uncertainties affecting the generation inflows are not addressed, that is, the generation pattern remains unchanged over the planning horizon. In this case, the solution requires the inclusion of the following equipments:

- Year 1 - one 138 kV line connecting buses 2 and 6 and another one connecting buses 7 to 8, one 138 kV cable in branch 6-10 and one transformer from bus 9 to 11;
- Year 2 - one 230 kV line connecting buses 11 to 13 and one transformer between buses 3 and 24;
- Year 4 - one 138 kV line connecting buses 5 to 10;
- Year 8 - one 138 kV line connecting bus 1 to 5;
- Year 9 - one 138 kV line connecting buses 3 and 9.

This solution ensures a safe operation, that is, a zero value for PNS, only if the generation pattern does not change over the planning horizon. Fig. 6 shows the behavior of the best solution in the swarm over the iterations for this deterministic approach. In this case the investment cost is $0,28.10^9$ \$.

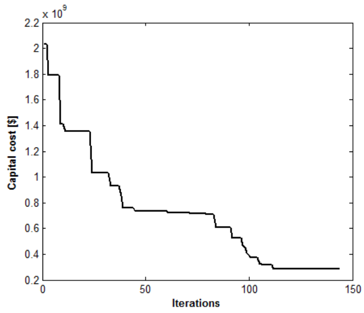

Figure 6. Evolution of the best particle – Deterministic approach.

In order to turn this comparison meaningful, the above deterministic solution was checked against the 20 scenarios considered before in order to calculate the expected PNS for each hydro inflow pattern. Fig. 7 shows the expected PNS for each of these scenarios considering the transmission expansion solution provided by the deterministic approach.

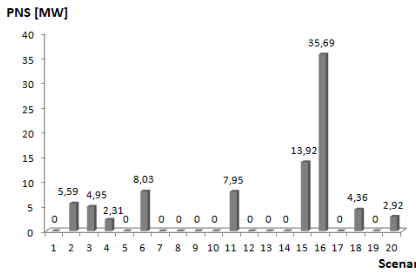

Figure 7. Expected PNS for the deterministic solution in each scenario.

Although the investment cost of the deterministic solution is lower than the obtained with the probabilistic approach, the annual deficit risk of the system is 45% against 5% of the probabilistic approach. This means if we consider the expected load shedding cost as used in (2), the average total cost for the deterministic solution considering the 20 hydro inflows is $4,56.10^9$ \$.

Regarding the parallel computing technique used to implement the EPSO algorithm, we use eight cores of an Intel i7, 3.4GHz, 8 GB RAM. Fig. 8 shows the gain in seconds for each iteration when EPSO is implemented using parallel computing (EPSO-PC). As mentioned before, the probabilistic TEP using parallel computing runs 138 iterations in about 22 hours. Not using parallel computing requires a total of 74 hours, which means that the parallel implementation is able to reduce the computation time by about 70%.

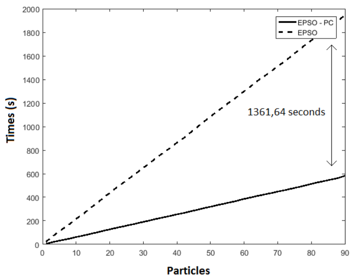

Figure 8. Gain time when using parallel computing to implement EPSO.

VI. DISCUSSION AND CONCLUSIONS

This paper describes a probabilistic multiyear transmission expansion planning that uses evolutionary particle swarm optimization to solve it via a parallel computing approach as a way to reduce the convergence time. The develop approach models hydro uncertainties using inflow scenarios and it incorporates a risk index determining that a transmission expansion solution is considered as feasible if, and only if, it ensures the safe operation in at least a percentage of these scenarios. For instance, if 20 scenarios are used, and the annual deficit risk index is set at 5% then the solution should ensure a safe operation, that is, zero PNS in 19 scenarios.

The main motivation to develop this probabilistic TEP approach comes from the need to deal with generation uncertainties affecting hydrothermal systems mainly from the climatic phenomena which can determine dry conditions in one region while there is increasing rainfall in another one. This type of systems usually requires a large amount of investments in transmission equipments in order to being able to accommodate different types of generation patterns.

The simulations performed using a system based on the IEEE 24 bus RTS network and the comparisons done in terms of the solution obtained by the probabilistic model and by a deterministic approach highlight the robust nature of the probabilistic based solution in terms of ensuring a safe operation in the lager majority of hydro scenarios although having larger investment costs. As a result, the authors are confident that TEP models based in these concepts can become a contribution to achieve large security of supply levels over the long run in power systems subjected to relevant uncertainties, namely affecting the generation patterns.

ACKNOWLEDGMENTS

The first author thanks CAPES Foundation, Ministry of Education of Brazil, for financing this research.

This work is financed by the ERDF – European Regional Development Fund through the Operational Programme for Competitiveness and Internationalisation - COMPETE 2020 within project «POCI-01-0145-FEDER-006961», and by National Funds through FCT – Fundação para a Ciência e a Tecnologia (Portuguese Foundation for Science and Technology) as part of project UID/EEA/50014/2013."

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BIOGRAPHIES

P. Vilaça Gomes (S'14) received the B.Eng. degree in electrical engineering from Federal University of Juiz de Fora, Brazil in 2014. He is currently pursuing the Ph.D. degree at the Faculty of Engineering of University of Porto, Portugal. He is also a researcher at INESCTEC, Portugal, on topics related with mathematical optimization and artificial intelligence applied in power system planning and reliability.

J. T. Saraiva (M'00) was born in Porto, Portugal in 1962. In 1987, 1993 and 2002 he got his MSc, PhD, and Agregado degrees in Electrical and Computer Engineering from FEUP, where he is currently Professor. In 1985 he joined INESC Porto – a private research institute – where he was head researcher or collaborated in several projects namely in the scope of consultancy contracts with the Portuguese Electricity Regulatory Agency and generation, transmission and distribution companies.

B.0.8 Impact of Large Fleets of Plug-in-Electric Vehicles on Transmission Systems Expansion Planning. (IEEE Power Systems Computation Conference, 2018)

Impact of Large Fleets of Plug-in-Electric Vehicles on Transmission Systems Expansion Planning

P. Vilaça Gomes, J. T. Saraiva and M. D. P. Coelho
INESC TEC and Faculty of Engineering of University of Porto, Portugal
phillipe.gomes@fe.up.pt

B. H. Dias, L. Willer, A. C. Junior
Faculty of Engineering of Federal University of Juiz de Fora, Brazil

***Abstract*— Electric vehicles will certainly play an important and increasing role in the transport sector over the next years. As their number grows, they will affect the behavior of the electricity demand seen not only by distribution but also by transmission networks and so changes will also occur in the operation and expansion planning of the power systems. In this sense, this paper addresses the impact of large fleets of Plug-in-Electric Vehicles (PEVs) in transmission equipment investments. The developed model uses evolutionary particle swarm optimization (EPSO) to handle the planning problem over different scenarios regarding the evolution of PEVs and their impact on the demand. These scenarios consider the PEVs penetration level, the availability of charging and the related charging policies. The paper includes a Case Study based on the IEEE 24 busbar power system model for a 10-year period. The model uses an AC Optimal Power Flow to analyse the operation of the system for different investment paths over the years and the results show that coordinating the charging of PEVs can be an interesting solution to postpone the investments in transmission equipment thus reducing the associated costs.**

***Index Terms*— Transmission Expansion Planning, Plug-in-Electric Vehicles, Evolutionary Particle Swarm Optimization, Parallel Computing, AC-Optimal Power Flow.**

NOMENCLATURE

Indexes:

b	Index for bus
p	Index for period
it	Index for iteration
*	Index for a mutated parameter

Parameters:

d	Discount rate
nb	Number of buses
np	Number of periods
β	Penalization factor for PNS

Variables:

C_{inv}	Investment cost
$Gbest$	Best solution found by the swarm
M	Scenarios of availability of charging
N	Diagonal matrix containing n
N_o	Diagonal matrix containing n_o
n	Equipment inserted into the system
n_o	Equipments on the base topology
pbest	Best solution found until the current iteration
P	Communication factor
P_D^b, Q_D^b	Real and reactive power demand vectors
P_G^b, Q_G^b	Real and reactive power generation vectors
PNS	Power not supplied
$rand()$	Random number between 0 and 1
$round()$	Rounding operator
S	Apparent power
V	Voltage magnitude vector
V	Particle velocity
W	Weights for the EPSO
X	Particle position
α	Variable used in the AC-OPF model to represents the load reduction
κ	Coefficient of present-worth value
θ	Bus angle vector

I. INTRODUCTION

A. Motivation

The electrification of the transport sector conjugated with the decarbonization of the electricity industry is one of the most important keys to achieve meaningful reductions of carbon dioxide emissions [1]. However, the increasing number of electric vehicles (EVs) changes the daily system demand and surely it must be considered when planning both distribution and transmission grids. The projections for the penetration of EVs are increasingly positive especially in countries such as USA, Germany, Spain, UK, Norway, Portugal and Greece [2]. For instance, the Electric Power Research Institute expects that by 2020 up to 35% of the new USA vehicles will be electric [3].

Nowadays, a very frequent question addresses how the EVs will affect the investments in distribution networks and indirectly in transmission networks. On the other hand, the impact of EV fleets depend on issues such as the mobility patterns, the traveled distances and the EV owner profiles. This increases the complexity of the analysis suggesting that deterministic approaches fail to capture the stochastic behavior of EV uses and therefore will produce insufficient results [2].

Distribution and transmission expansion planning are usually performed considering a forecasted demand over a planning horizon. From this possible demand evolution, it is extracted the worst case to be used in the planning exercises. This worst case is associated with the annual peak demand that typically occurs in a few hours of the year. In this sense, EVs can be used to smooth the demand and to postpone investments in new grid equipments namely if they are seen as controlled loads (G2V) and controlled sources (V2G) [4]. Nevertheless, expansion planning studies already have to deal with uncertainties related to the demand growth, distributed generation, the generation capacities and the availability of transmission and generation facilities. Now, the advent of EVs introduce a new level of uncertainty related with the charging and discharging patterns of the EV batteries.

Having in mind the previous aspects, the research work reported in this paper describes a new methodology capable of identifying the impact of EVs on equipment investments in transmission grids having the following main characteristics:

- Multi-year nature in order to accurately represent the year-by-year investment decisions;
- True mathematical representation of the network operation using an AC OPF model;
- Different scenarios of EVs penetration, charging policies and availability of charge.

B. Literature Review

Although the importance of planning considering EVs is clearly a relevant issue, to the best knowledge of the authors, Transmission Expansion Planning (TEP) considering the penetration of EVs are just studied in [5], [6]. Both papers model the TEP problem using a static approach in which each period is treated separately and sequentially so that investments selected in one period will then be considered in operation in the next ones. This is a very simplified way of treating TEP problems since the holistic view over the entire horizon is lost. In this sense, dynamic models preserve this holistic view related with the year-by-year representation of investment decisions as described in [7]–[9]

Apart from using static models, these publications [5], [6] introduce another relaxation of the true problem because the operation of the system is analysed in a simplified way based on a DC model that disregards transmission losses, reactive power flows and the bus voltage limits. Despite the mentioned drawbacks, the DC model has been widely used in the literature for mathematical modeling of the TEP problem, as in [10], mainly due to the more reduced computational effort required by this model. However, the DC model does not guarantee that the optimum solution of the simplified (relaxed) problem is even feasible if it is tested on the real full AC problem. Differently, AC based models are able to represent the true behavior of the grid as described in [11] that details a TEP approach using an AC Optimal Power Flow, AC-OPF).

In addition to the publications mentioned before, the work performed (using the Irish regional case study) in the frame of *European GridTech project* (www.gridtech.eu) was conducted considering EVs on TEP. Besides, [2], [4] describe the evaluation of impact of EVs on the system demand, namely in a smart grid environment in the second case. In [4], the use of Plug-in-Electric Vehicles (PEVs) is investigated on a distribution grid. In [12], a new power flow model with PEVs based on their traffic flow is proposed. The model is applied to a distribution grid and considers different travel patterns, purposes and charging infrastructure.

As described in [13], large fleets of PEVs can be beneficial because they can consume excess of generation, eventually from renewable sources, in off-peak periods and they can provide some services during peak hours [13]. However, when they are in the charging mode and specially if a completely uncontrolled charging policy is used then the peak demand seen by distribution grids can increase eventually requiring extra very costly investments [14].

C. Contribution and Structure

This work addresses the impact of Plug-in-Electric Vehicles in transmission expansion planning. Several scenarios for the penetration level, charging policies and availability of charging are considered to estimate the impact of PEVs on transmission grid investments. The approach uses a computational intelligence tool to deal with the dynamic and multiyear nature of investment decisions and it takes into account the true behavior of the grid through the AC-model.

This paper is organized as follows: Section II describes the effects of PEVs on the system demand, Section III describes the developed TEP formulation and Section IV details the evolutionary particle swarm optimization (EPSO). Section V presents the results of the numerical simulations and Section VI includes some comments and the conclusions of this work.

II. PLUG-IN.ELECTRIC VEHICLES AND THEIR IMPACTS ON THE SYSTEM DEMAND

Electric vehicles are commonly characterized as vehicles that use an electric motor to hand over mechanical shaft power [15]. PEVs have different demands depending on their technology and they change the system demand according to the different needs of their owners, the charging policies that are used/proposed by electricity retailers, the level of penetration and the availability of charging. This section briefly discusses the different variables that influence the impact of the PEVs on the system demand.

A. PEVs Penetration

The PEVs penetration must be predicted along the planning horizon as well as the location of future charging stations. The network needs to be prepared to meet this new future demand which means that this information has to be internalized in expansion and operation planning studies. PEVs penetration scenarios are a key element to identify their charging impact on the grid. Besides, due to its behavior as

V2G or G2V, proper business models should be proposed and adopted to model the controllability of EVs.

In this paper, three levels of PEVs penetration are admitted: the most likely level, the optimistic one and the aggressive level. The expectation of PEVs penetration in Europe indicates that by 2030 the sales will reach 15% of the total new sold vehicles. In the optimistic and aggressive scenarios, this value rises to 30% and 50%, respectively [2].

B. *Charging Policies*

The charging policies have a direct influence on the decision of the PEVs owner, although sometimes this decision is transferred to a third agent called parking lots [16]. In this case, the PEVs user must indicate the level of energy that must be stored during a specific time. Among the various classifications of charging strategies, the present study addresses the following policies:

- Uncontrolled charging;
- Multiple Tariffs;
- Smart charging;
- V2G services.

In the uncontrolled charging, PEV owners connect the vehicle to the grid when the last trip is finished or when a charging point is available. In the multiple tariffs policy, the retailer offers different tariff levels (peak periods with higher prices and off peak with lower prices) to induce consumers to shift the demand to off-peak. In the smart charging, the retailer or the grid operator control the time and the charging process of the PEVs and as a result generally smart charging leads to a valley-filling effect. Finally, V2G services are an extension of smart charging with a peak shave effect, that is, the available PEVs can sell energy stored in the battery to the system [2].

C. *Availability of Charging*

The charging infrastructure has to be considered given its impact on the system. The results of the studies on the penetration of PEVs should be used to ensure that the infrastructure is available while it is also true that the availability of such an infrastructure can increase the confidence level of consumers and so contribute to increase the penetration level. In this paper, we consider four different models for the availability of charging corresponding to 100%, 75%, 50% and 25% of charging at home while the remaining charging is done when arriving to the work.

III. PLANNING FORMULATION

The proposed methodology considers different scenarios for the penetration level, the charging policies and the availability of charging. The demand from EV charging is assessed along the horizon combining these scenarios and then the results are added to the hourly demand forecast for the same period as shown in Fig.1. Using a worst-case approach, from the hourly demand along the horizon, it is extracted the annual peak demand for each year to run the TEP exercise to get information on the impact of PEVs on grid investments.

A. *Mathematical Formulation of the Planning Problem*

The mathematical model discussed in this paper considers the dynamic nature of investment decisions and the true representation of the network using an AC-OPF model. In general, the TEP problem can be formulated by (1) to (4). Physical constraints are associated to the generator, nodal voltages and branch capacity limits, financial constraints refer to the maximum amount that is available to be invested in a planning period and the quality of service constraints are related to limits imposed to reliability indexes.

$$\text{Minimize Objective Function} \tag{1}$$

Subject to:

$$\text{Physical Constraints} \tag{2}$$

$$\text{Financial Constraints} \tag{3}$$

$$\text{Quality of Services Constraints} \tag{4}$$

The objective function to be minimized in this study is the investment cost in new transmission equipment (5) in which κ_p is the present-worth value coefficient given by (6).

$$\sum_{p=1}^{np} \kappa_p . C_{inv}(p) + \beta . PNS(p) \tag{5}$$

$$\kappa_p = \frac{1}{(1+d)^p} \tag{6}$$

The investment cost in each period is the sum of the costs of new equipment inserted in the system in that period. The objective function also includes a penalization on PNS for solutions that cannot meet the peak load. PNS is obtained solving the AC-OPF given by (7) to (16).

$$Min\ PNS = \sum_{b=1}^{nb} (1-\alpha_b).P_D^b \tag{7}$$

subject to

$$P(V,\theta,n)_b - P_G^b + \alpha_b . P_D^b = 0 \tag{8}$$

$$Q(V,\theta,n)_b - Q_G^b + \alpha_b . Q_D^b = 0 \tag{9}$$

$$P_{G\min}^b \le P_G^b \le P_{G\max}^b \tag{10}$$

$$Q_{G\min}^b \le Q_G^b \le Q_{G\max}^b \tag{11}$$

$$V_{\min} \le V \le V_{\max} \tag{12}$$

$$(N+N_o)S_{from} \le (N+N_o)S_{\max} \tag{13}$$

$$(N+\overset{o}{N})S^{to} \le (N+\overset{o}{N})S_{\max} \tag{14}$$

$$0 \le n \le n_{\max} \tag{15}$$

$$0 \le \alpha_b \le 1 \tag{16}$$

In this approach, the loads are modeled with a flexibility variable, α, which means the problem has enough flexibility to reduce the demand in node b if this is required to maintain feasibility. Additionally, if an active load reduction is needed, then the reactive demand is also reduced in the same proportion to keep the power factor unchanged. Apart from active and reactive balance equations and limit constraints for active and reactive generation and voltages, constraints (13) and (14) ensure that the apparent power flow in a branch complies with the limits of the transmission lines.

3

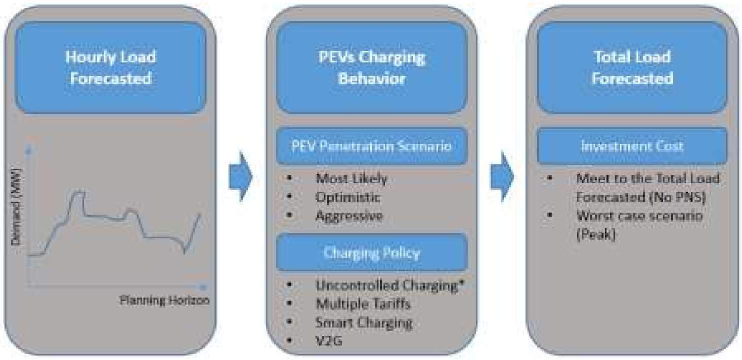

Figure 1: Proposed methodology.

IV. Evolutionary Particle Swarm Optimization

As the planning problem considers scenarios for the PEVs charging policies, availability of charging and penetration level, the TEP problem is solved 22 times (21 scenarios associated to the PEVs and a base case scenario not considering PEVs). Therefore, a powerful tool must be used due to the required high computational effort. In this sense, EPSO is a metaheuristic that combines concepts of evolutionary computation and multi-agent population taking advantage of the standard blocks that are typical in Genetic Algorithms and Particle Swarm Optimization [17]. The pseudo-code for a general EPSO is detailed below.

Pseudo-Code 1: EPSO Algorithm

```
Set the number of particles in the swarm.
    While convergence criterion is not satisfied
        For each iteration
            Replication block – Clone the population r times
            Mutation block – Eq. (17) and Eq. (18)
            Recombination block – Eq. (19) and (20)
            Evaluation block – The population is evaluated
            according to its own fitness function - Eq. (5).
            Selection block – Tournament selection
        End for
    End while
```

EPSO starts with an initial population that is randomly created looking at a tabu list to prevent repeating the same particle in the population and then increasing the diversity of the particles. In the replication block, the population is cloned a predefined number of times and these clones are changed in the mutation block using the weights given by (17). The best particle so far obtained also undergoes mutation using (18).

$$\overset{*}{w}_{ij}^{it+1} = 0.5 + rand() - \frac{1}{1+e^{-\overset{*}{w}_{ij}^{it}}} \tag{17}$$

$$\overset{*}{gbest} = gbest + round(2.\overset{*}{w}_{i4}^{it+1} - 1) \tag{18}$$

After the mutation block, new offsprings are created based on the PSO movement rule. In iteration it+1, the new position of particle i is given by (19) given its position in iteration it plus the velocity term determining the move from iteration it to it+1. The velocity is given by (20) in which the first term refers to the inertia of the particle determining a movement in the same direction as in the previous iteration. The second term refers to the "cognitive" part, which represents the individual knowledge of the particle acquired over the search process in the sense that this term corresponds to best particle in position i that was obtained so far. The third term refers to the "social" part, which corresponds to the collaboration among the particles, i.e, the collective knowledge gained by the swarm throughout the search process. This term induces a movement towards the best participle so far obtained in the entire population. The communication factor P in (20) is used to control the information transmitted by the particles about the collective knowledge inside the swarm [18].

$$x_i^{it+1} = x_i^{it} + v_i^{it+1} \tag{19}$$

$$v_i^{it+1} = \overset{*}{w}_{i1}^{it+1}.v_i^{it} + \overset{*}{w}_{i2}^{it+1}.(pbest_i - x_i^{it}) + \overset{*}{w}_{i3}^{it+1}.(gbest - x_i^{it}).P \tag{20}$$

Each particle in the population is then evaluated using (5) after characterizing all the particles by their investment and power not supplied costs. Then, a tournament selection is used to build the new population having the same size of the initial one. The iterative process continues until best solution remains unchanged along a pre-defined number of iterations.

Considering a population of 30 particles, using 3 clones in each iteration and having a planning horizon of 10 years, EPSO requires running in each iteration a total of 900 AC-OPFs given by (7) to (16). Considering that the average number of iterations before stopping is 30 in each TEP exercise and that this problem is solved for 22 scenarios, the number of solved AC-OPFs is about 595 thousand.

V. Numerical Simulations

A. Outline of the Tests

As the number of AC-OPFs required to calculate the *PNS* values is large, in this paper we used the interior point method option to solve the problem (7) to (16) available in the solver [19]. Besides, in order to reduce the computational time that is required, all the simulations were running using parallel computing in MATLAB on an Intel i7, 3.4GHz, 16 GB RAM.

B. General Data

The planning horizon includes 10 years and in the simulations we used a penalization factor for *PNS* equal to 10^9 \$/MW, the number of particles in the population was set at 30 particles, a discount rate of 5% and a load growth of 2.5% per year were admitted. The modified IEEE 24 busbar power system model available in [17] was used in the simulations since this system has detailed hourly demand available in [20]. Besides, the scenarios for the PEV evolution and its impact on the system demand were extracted from [2] using the German case in which a stochastic EV demand simulation methodology was employed on an hourly basis. The penetration scenarios considered are indicated in Table I and the scenarios for charging availability (only considered for uncontrolled charging) are presented in Table II. Finally, in the multiple tariffs scenario we specified that the low tariffs period goes from 22h to 06h.

TABLE I. PEVS PENETRATION SCENARIOS

	Penetration Scenarios over the Planning Horizon		
	Likely	*Optimistic*	*Aggressive*
PEVs	414.000	847.000	1.728.000

The additional demand for each of the 21 scenarios is displayed in Fig. 2. These values are calculated for the last year in the horizon when the cumulative PEV penetration assumes the largest value.

TABLE II. AVAILABILITY OF CHARGING

Availability of Charging for Uncontrolled Charging			
Model 1 (M1)	*Model 2 (M2)*	*Model 3 (M3)*	*Model 4 (M4)*
100% Home	75% Home 25% Work	50% Home 50% Work	25% Home 75% Work

Before running the planning exercise for each scenario, it is still necessary to obtain the impact on the system demand for each scenario on an hourly basis for the entire planning horizon. For illustration of how the PEVs change the electricity demand, the impact of each scenario on a peak day of the original base case (without PEVs) in the 10th year is shown in Fig. 3. After getting the hourly demand, it is then obtained the annual peak demand along the 10-year horizon to be used in the TEP exercise. The annual peak demand for each scenario is shown in Fig. 4. This figure also shows that in some scenarios the demand will exceed the generation capacity indicating that a generation expansion planning (GEP) study should also be considered.

Finally, the TEP problem is conducted for each of the 21 scenarios under study and for the base case in which no PEVs were considered. For the Base Case the investment cost in new transmission equipment is 0.32 million USD and the global investment cost for each scenario are presented in Tables III and IV. It should be noticed that in some scenarios, TEP is not run because the demand in these scenarios cannot be met only with new transmission equipments since new generation units also have to be installed.

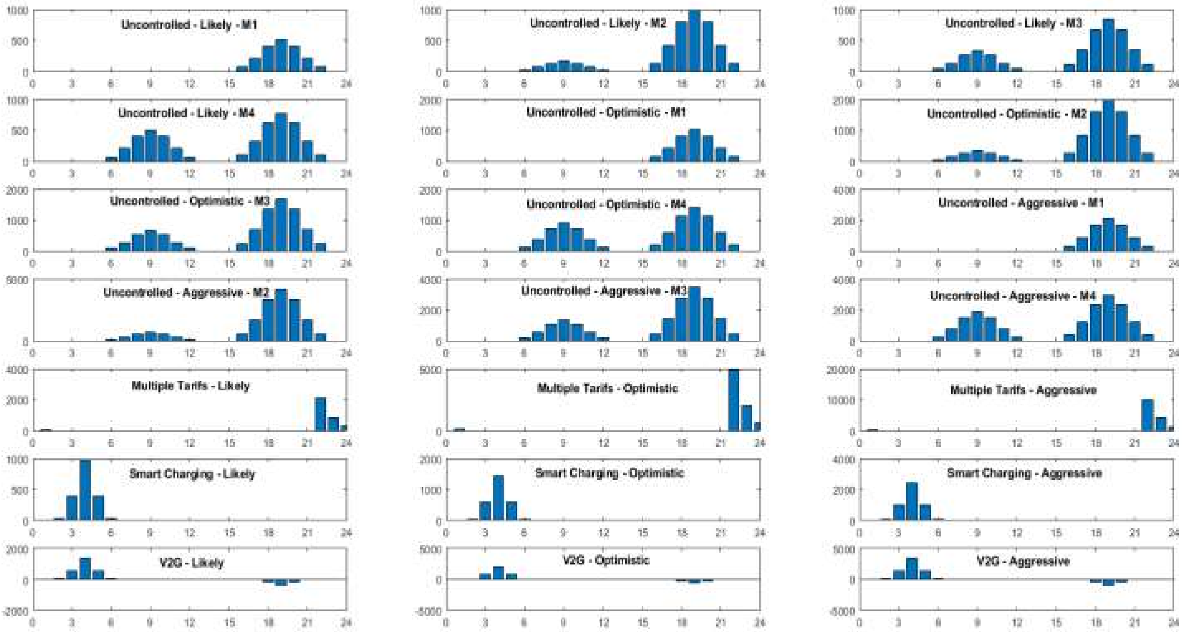

Figure 2: Impact of PEVs on the system demand (horizontal axes in hours and vertical axes in MW)

5

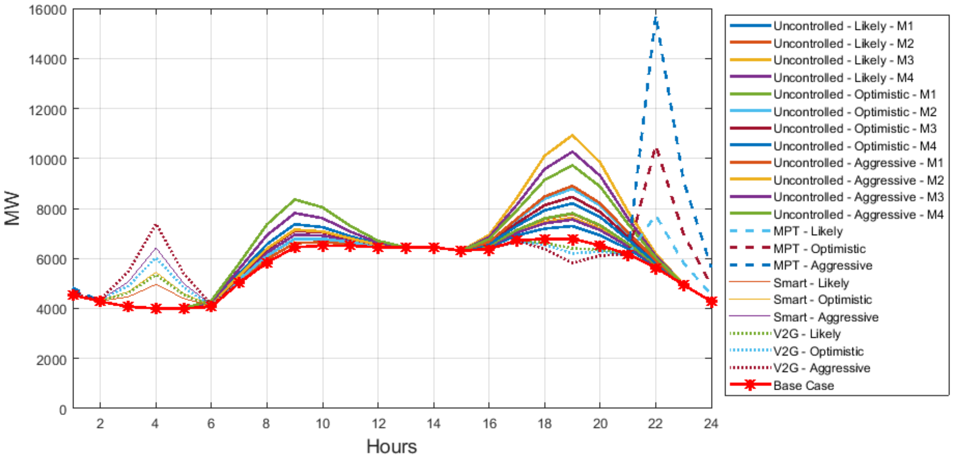

Figure 3: Impact of each PEVs scenario over a day in the 10th year.

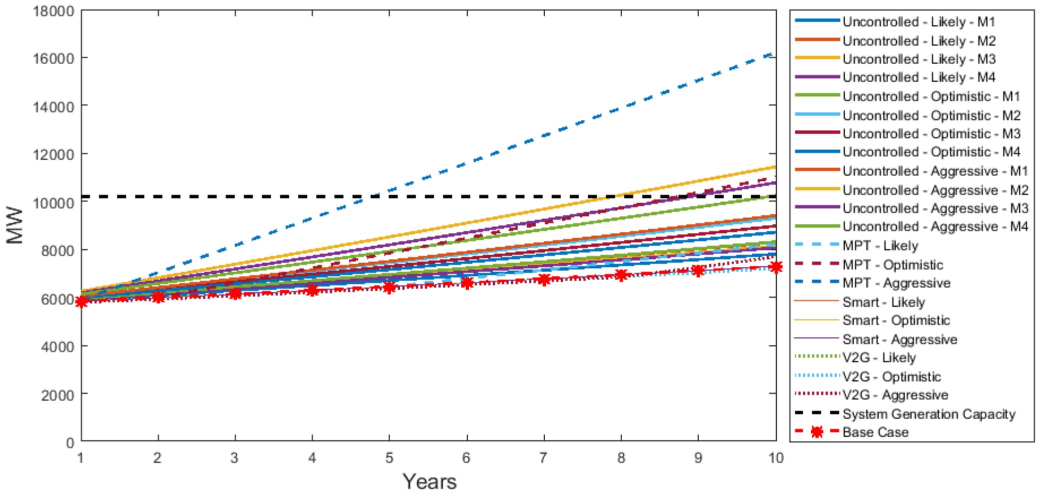

Figure 4: Peak demand for the different scenarios of PEVs (system generation capacity in black dashed line)

TABLE III. INVESTMENT COSTS – UNCONTROLLED CHARGING (10^6 USD)

Uncontrolled Charging				
	M1	M2	M3	M4
Likely	0.50	0.91	0.93	0.99
Optimistic	1.13	1.35	1.60	2.12
Aggressive	1.31	GEP	GEP	GEP

TABLE IV. INVESTMENT COSTS – MULTIPLE TARIFFS, SMART CHARGING AND V2G (10^6 USD)

	Multiple Tariffs	**Smart Charging**	**V2G**
Likely	1.91	0.53	0.31
Optimistic	GEP	0.65	0.38
Aggressive	GEP	0.92	0.84

6

VI. CONCLUSIONS

Plug-in-electric vehicles will certainly represent an important contribution to tackle environmental issues, but it is also clear that their introduction in power systems is bringing several challenges. PEVs can be seen as controlled loads and/or as controlled sources and these characteristics can be used in profitable way to help accommodating increasing amount of electricity injections from intermittent sources. Therefore, new storage resources can be beneficially used, and PEVs can be an important resource in this path if adequate business models ensure the remuneration of their owners. Although PEVs are primarily intended for transport, charging strategies must be addressed so that the electric demand does not present peaks too large than today given the impact this might have on network infrastructures. Therefore, an efficient management approach to control PEVs charging must include the "valley-filling effect" and the "peak-shaving effect". In other words, PEVs should charge during the off-peak periods and used as sources in peak periods.

Having in mind these aspects and effects, this paper reports the results obtained when studying the impact of the penetration of large fleets of PEVs in the investment in new transmission equipment. In this paper, we considered several scenarios to represent the penetration level, the charging policies and availability of charging. The impact on the hourly system demand is carried out for the next 10 years for each of these scenarios and then the TEP is solved for each scenario considering the peak demand on each year of the horizon. As indicated in Section III, the TEP exercise was conducted using an AC-OPF model and an EPSO technique.

The TEP results reported in Section V confirm that uncontrolled charging policy is likely to increase the peak demand and therefore requires more transmission investments over the years. The adoption of a multiple tariff scheme has a strong impact on the demand profile namely because there in practice a strongly filling effect on the initial hours of the original valley period (that is, on the two or three hours immediately after 22.00). As a result, this concentration effect originates a large increase of the required investments on the transmission system. Considering the required transmission investments, smart charging is a good option given that PEVs are charged when that is more adequate. However, if V2G is implementable given the required business models and communication infrastructures then we obtain the most reduced transmission investment costs because PEVs can contribute to supply the demand using a portion of the energy stored in their batteries.

ACKNOWLEDGMENT

This work is financed by the ERDF – European Regional Development Fund through the Operational Programme for Competitiveness and Internationalisation - COMPETE 2020 Programme within project «POCI-01-0145-FEDER-006961», and by National Funds through the Portuguese funding agency, FCT - Fundação para a Ciência e a Tecnologia as part of project «UID/EEA/50014/2013».

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B.0.9 A novel efficient method for multiyear multiobjective dynamic transmission system planning. (International Journal of Electrical Power & Energy Systems, 2018)

Electrical Power and Energy Systems 100 (2018) 10–18

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

A novel efficient method for multiyear multiobjective dynamic transmission system planning

P. Vilaça Gomes*, João Tomé Saraiva

Faculty of Engineering of the University of Porto, Institute for Systems and Computer Engineering, Technology and Science – INESC TEC, Portugal

ARTICLE INFO

Keywords:
AC optimal power flow
Expected power not supplied
MEPSO-II
Monte Carlo simulation
Multiobjective transmission expansion planning
Uncertainties

ABSTRACT

The unbundling of the electricity sector in several activities, some of them provided in a regulated way and some others under competition, poses a number of challenging problems namely because in several areas there are conflicting objectives associated to different stakeholders. These different views and objectives paved the way to the development of new multiobjective tools able to represent this new paradigm. In this scope, this paper presents a multiobjective (MO) formulation for the Transmission Expansion Planning (TEP) problem using a new solution approach that combines concepts of evolutionary computation and multi agent population algorithms. The new proposed tool is termed as Multi-Population and Multiobjective Evolutionary Particle Swarm Optimization - MEPSO-II. The TEP problem is handled in a realistic way preserving the holistic view over the entire planning horizon and the true grid behavior because it considers the multi-stage nature of the problem and we use an AC Optimal Power Flow (AC-OPF) model to gain insight on the operation conditions of the network. The multi objective formulation considers the total system cost, on one side, and the Expected Power Not Supplied (EPNS), on the other. The total system cost comprises the investment cost in new equipment and the operation costs while the EPNS takes into account the uncertainties related to the non– ideal behavior of system components using a non-chronological Monte Carlo simulation. Numerical simulations are conducted using the IEEE 24 and the 118 Bus Test Systems in order to compare the proposed MO tool against other algorithms through performance evaluation indices. Although being a higher time-consuming tool, the MEPSO-II enables improving the Pareto-Front and therefore it gives more insight to transmission network planners when compared with other consolidated algorithms described in the literature.

1. Introduction

1.1. Motivation

Transmission grid expansion planning is becoming increasingly complex due to the unbundling and restructuring of the electricity sector as well as due to environmental concerns. The unbundling of the electricity business leads to multiple and conflicting objectives associated to different stakeholders and extra financial and physical uncertainties [1]. The growing environmental concerns widened the path to the large-scale use of renewable primary sources, several of them characterized by their intermittency, that have been gaining more and more space in the global energy matrix. A large amount of these units is connected to distribution networks or even at the end user installations contributing to modify the traditional generation-transmission-load patterns to be considered in transmission planning studies. The restructuring of the global power industry contributed to change long term established planning practices, since investors in generation are free to decide when and where to invest in new facilities and the presence of generation sources using volatile resources as wind and solar units introduced new types of uncertainties in planning problems. These changes turned less adequate traditional planning approaches only based on the identification of the lowest investment cost expansion strategies and plans.

As an answer to these changes, in recent years new multiobjective models and solution approaches as the ones in [2–4] were developed instead of considering just one objective as in classical optimization approaches. Nevertheless, TEP has some peculiarities that contribute to turn the development of new tools more difficult such as [5]:

- Non-convex search space, so that solution algorithms may converge to local optima.
- Integer nature leading to the phenomenon of combinatorial explosion of investment alternative plans. This characteristic usually requires a high computational effort to identify good quality plans.
- In some cases, there are isolated smaller systems that should be

* Corresponding author at: Rua Dr. Roberto Frias, 4200-465 Porto, Portugal.
E-mail address: phillipe.gomes@fe.up.pt (P. Vilaça Gomes).

https://doi.org/10.1016/j.ijepes.2018.02.020
Received 12 October 2017; Received in revised form 19 December 2017; Accepted 8 February 2018
Available online 21 February 2018

Nomenclature

Indices

b	index for bus
eq	index for equipment
i	index for individual
it	index for iteration
k	index for the weights for the MEPSO-II tool
p	index for period
st	index for system states
*	index for mutated parameter

Parameters

nb	number of buses
neq	number of equipment
d	discount rate
FOR	forced outage rate
np	number of periods
Nst	number of system states
OF	objective function
P	communication factor
T_{eq}^{com}	commissioning time
β	penalization factor for PNS

Variables

C_{inv}, C_{op}	investment and operation costs
D	distance between consecutive solutions
Dm	mean of all D
e, ER	error ratio parameter and Error Ratio
ed	Euclidian distance
$EPNS$	Expected Power Not Supplied
$gbest$	best solution found by the swarm
GD	general distance
K	coefficient of present-worth value.
npf	number of solutions in each Pareto-Front
n_{kj}	inserted equipment between bars k and j
$\overset{o}{n}_{kj}$	equipment on the base topology (between bars k and j)
N	diagonal matrix containing n_{kj}
$\overset{o}{N}$	diagonal matrix containing $\overset{o}{n}_{kj}$
$pbest$	best solution found until the current iteration
PF	Pareto-Front
PFR	Pareto-Front rate
P_D, Q_D	real and reactive power demand vectors
P_G, Q_G	real and reactive power generation vectors
PNS	Power Not Supplied
r	number of clones in the MEPSO-II tool
$rand()$	random number between 0 and 1
$round()$	rounding operator
S	apparent power
U	equipment availability
v	particle velocity
V	voltage magnitude vector
w	weights for the MEPSO-II tool
x	particle position
θ	bus angle
δ	equipment investment state
ε	uniformly distributed random number
α_b	variable used in the AC-OPF model to represent the load shedding in bus b

Sets

Ω	set of candidate equipment

connected to the main system and this can originate convergence problems.

Having in mind these difficulties and challenges, the research work reported in this paper describes a new efficient methodology capable of dealing with the mentioned drawbacks and considering the following characteristics:

- Multi-year nature that can accurately represents the multi-stage characteristics of investment decisions.
- True mathematical representation of the network using an AC formulation.
- Multiobjective formulation and solution approach.
- Uncertainties inherent to the long-term planning problems.

1.2. Literature review

The multiyear (or dynamic) nature of TEP problems requires considering in the same run several sub-periods over the planning horizon in order to identify a set of new equipment (transmission lines, cables or transformers) with the respective insertion times on the grid as described in [6,7]. This nature brings the benefit of preserving the holistic view over the planning horizon, but it also increases the computational burden of the problem in a way that it can become prohibitive. Up to now, dynamic TEP is performed just in small case studies that do not correspond to real systems [8]. Therefore, the TEP problem is often addressed in a simplified way also known as static approach as in [9–11]. In these cases, each period is treated separately and sequentially so that investments selected in one period will then be considered in operation in the next ones.

In order to further reduce the computational burden, the mathematical model of the TEP problem can also be relaxed using, for instance, the DC power flow model. This relaxation turns the TEP problem more manageable as suggested in [12]. Although this was a widely used approach both in academia and industry, this type of models does not guarantee that the optimum solution of the modified (relaxed) problem is feasible regarding the real problem. Furthermore, TEP DC and AC formulations were compared in [13,14] and the results indicate that the TEP using DC models often provide underestimates for the grid investment costs and additionally the associated expansion plans can produce violations of the true AC grid constraints. Differently from the DC based models, TEP AC models take into account the reactive power, the losses and the voltage limits on the bars, turning these models more adequate to reflect in a realistic way the operation conditions of the network [15].

The restructuring of the electricity sector brings additional challenges to transmission planers once TEP models should be able to meet the goals of different stakeholders as, for instance, improving the competition among electricity market agents, alleviating transmission congestion, minimizing the risk of investments, minimizing the investment and operation costs and maximizing system reliability [16]. Multi-objective (MO) approaches can provide information about the tradeoff between different conflicting objectives since MO problems do not have a single optimal solution, but they are typically associated to a set of non-dominated solutions – the Pareto-Front [17] among which the final decision should emerge. In this context, evolutionary algorithms started to be used to explore the Pareto-Front mainly because in each iteration they inherently provide a collection of points on the solution front [18] and the evolution on computer processing allows building fast and efficient solution codes even for complex problems such as the one addressed in this paper.

Although the large majority of models in TEP literature ignores uncertainties mainly because of the required computational burden, nowadays it is a common feature to internalize in TEP problems uncertainties affecting the demand growth and its spatial distribution, the generation capacities and the availability of transmission and generation facilities [8].

1.3. Relevance and contributions

The conflicting objectives associated to different stakeholders in the new unbundled and restructured electric sector and the peculiarities of the TEP problem turning the development of new tools a challenging task, are the major aspects of the present work. Therefore, this paper describes a new tool based on computational intelligence techniques in order to solve a multiobjective TEP formulation. This model and the associated solution approach allows better exploiting the search space, while it models the true behavior of the network using an AC based formulation, it represents the multi-year nature of investment decisions and internalizes the uncertainties related with the life cycle of system components.

The developed tool was applied to the IEEE RTS 24 Bus and to the IEEE 118 Bus Test Systems and the results are compared with the ones obtained by two other techniques described in the literature: The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [19] and the Multiobjective Evolutionary Particle Swarm Optimization (MEPSO) [2].

1.4. Structure

This paper is organized as follows. After Section 1, Section 2 details the multiobjective formulation of the planning problem, Section 3 describes the main steps of the proposed solution tool, Section 4 details the performance evaluation of multiobjective algorithms, Section 5 presents the results of the numerical simulations and Section 6 includes some comments and the conclusions of this work.

2. Mathematical formulation of the TEP problem

2.1. Multiobjective approach

When addressing the TEP problem, the planner usually prepares a list of candidate equipment (cables, transformers or new transmission lines) adequately characterized in terms of the associated nominal voltages and investment cost. Using this pre-defined list, the TEP problem has the purpose of identifying a subset of this list containing the equipment to be built and their commissioning dates so that some pre-defined objective functions (OFs) are optimized while supplying the forecasted demand along the planning horizon. Furthermore, the transmission planning analysis should also consider issues as security and reliability, which contribute to increase the complexity of the problem.

The mathematical model discussed in this paper takes into account the dynamic and multiobjective nature of power systems. The dynamic nature is related with the multiyear approach and the multiobjective formulation considers two goals as follows: the system total cost termed as OF_1, and the Expected Power Not Supplied (EPNS) termed as OF_2.

Therefore, the associated TEP problem can be formulated by (1)–(4). Physical constraints are associated to the generator and branch capacity limits, financial constraints refer to the maximum amount that is available to be invested in each planning period and the quality of service constraints are related to limits imposed to reliability indices as the maximum value allowed for PNS in normal or contingency regimes.

$$\text{Minimize } OF_1 \text{ and } OF_2 \tag{1}$$

$$\text{Subject to:} \quad \text{Physical Constraints} \tag{2}$$

$$\text{Financial Constraints} \tag{3}$$

$$\text{Quality of Services Constraints} \tag{4}$$

As mentioned above, in (1) OF_1 and OF_2 are the total system cost and the EPNS. These are conflicting objectives in the sense that reducing investments along time will tend to degrade the quality of service thus increasing the EPNS. This conflicting nature justifies the adoption of a multi objective approach to deal with this problem and not just simply adding these two functions in a single objective function using a cost for Power Not Supplied.

2.2. System total cost assessment

The system total cost comprises the investment costs and the operating costs over the planning horizon as presented in (5)–(8). In (5), κ_p is the present-worth value coefficient (6) and the investment cost $C_{inv,p}$ includes the cost of new equipment scheduled for period p. For each equipment eq, this cost is modeled using a binary variable δ that is 0 for the periods before the installation, respecting the commissioning time of that equipment, and is 1 from that period onwards according to (8) and (9). The operation cost $C_{op,p}$ (10) takes into account the cost of unserved demand in period p in which β is a penalization factor in case the plan under analysis cannot meet the inelastic demand, that is, if a non-zero value for Power Not Supplied (PNS) is obtained for that plan in period p.

$$OF_1 = \sum_{p=1}^{np} \kappa_p (C_{inv,p} + C_{op,p}) \tag{5}$$

$$\kappa_p = \frac{1}{(1+d)^p} \tag{6}$$

$$C_{inv,p} = \sum_{eq=1}^{neq} C_{eq,p}(\delta_{eq,p} - \delta_{eq,(p-1)}) \tag{7}$$

$$\delta_{eq,p} = 0\,, \quad \forall\, eq \in \Omega\,, \forall\, p < T_{eq}^{com} \tag{8}$$

$$\delta_{eq,(p-1)} \leqslant \delta_{eq,p}\,, \ \forall\, eq \in \Omega\,, \ \forall\, p \tag{9}$$

$$C_{op,p} = \beta \cdot PNS_p \tag{10}$$

In order to compute the PNS for the topology of the system that is in service in each period p of the horizon and considering the new equipment included in the expansion plan under analysis, we used an AC-OPF based model given by (11)–(20).

$$Min\ PNS = \sum_{b=1}^{nb} (1-\alpha_b) \cdot P_D^b \tag{11}$$

$$\text{subject to } P(V,\theta,n)_b - P_G^b + \alpha_b \cdot P_D^b = 0 \tag{12}$$

$$Q(V,\theta,n)_b - Q_G^b + \alpha_b \cdot Q_D^b = 0 \tag{13}$$

$$P_{G\min} \leqslant P_G \leqslant P_{G\max} \tag{14}$$

$$Q_{G\min} \leqslant Q_G \leqslant Q_{G\max} \tag{15}$$

$$V_{\min} \leqslant V \leqslant V_{\max} \tag{16}$$

$$(N + \overset{o}{N})S^{from} \leqslant (N + \overset{o}{N})S_{\max} \tag{17}$$

$$(N + \overset{o}{N})S^{to} \leqslant (N + \overset{o}{N})S_{\max} \tag{18}$$

$$0 \leqslant n \leqslant n_{\max} \tag{19}$$

$$0 \leqslant \alpha_b \leqslant 1 \tag{20}$$

In this formulation, Eq. (11) is the objective function to be minimized, corresponding to the Power Not Supplied as a sum of demand curtailed in each bus *b*. Eqs. (12) and (13) are the real and reactive power balance equations, Eqs. (14) and (15) are the real and reactive power limit constraints, Eq. (16) is the voltage limit constraint, Eqs. (17) and (18) ensure that the apparent power flow in each branch complies with the transmission limits and Eq. (19) imposes the maximum number of new equipment to be inserted in a right-of-way. To ensure the convergence of the AC-OPF, the loads are considered dispatchable. In this approach, the loads are modeled with a flexibility variable, α, which means the problem has enough flexibility to reduce the demand in node *b* if this is required to maintain feasibility. Additionally, if an active load shedding is needed, then the reactive demand is also reduced in the same proportion to keep the power factor unchanged.

2.3. Expected power not supplied assessment

The EPNS used in OF_2 corresponds to the addition of the EPNS values estimated for each period of the planning horizon (21). For each period *p*, we use a non-chronological Monte Carlo Simulation (MCS) in order to generate states reflecting the life cycle of transmission lines, cables, transformers and generating units in terms of operation and failure periods. In each state some equipments are available and in operation while some others are affected by failures and the equipment random outages are obtained by sampling for each equipment a uniformly distributed random number ranging from 0 to 1. Therefore, an equipment is on outage if this sampled number is less than its associated Forced Outage Rate (FOR). In order to reduce the burden associated to the computation of the EPNS, we used the probability metrics based scenario reduction technique described in [20] that is reported to reduce the required number of analysed states by a factor of 100. This technique determines a subset of states to be analysed, with the correspondent probability of each one, ensuring that the states in this subset closely follow the probability distribution of the entire population of possible system states. Besides, in the multi-stage TEP, the number of equipments in the system changes along the years, so that the number of states to be analysed also varies from year to year. The EPNS for period *p* is then obtained using (22) and the main MCS steps are highlighted in the following pseudo-code.

$$OF_2 = \sum_{p=1}^{np} EPNS_p \tag{21}$$

$$EPNS_p = \frac{1}{Nst}\sum_{st=1}^{Nst} PNS_{st} \tag{22}$$

Pseudo-Code 1 (*Monte Carlo Simulation for EPNS*).

For each candidate plan
  Initialize FOR_{eq} and $U_{eq} = 1$ for all equipment *eq* and the number of outage states *Nst*
  For each outage states *st*
    Sample a uniformly distributed random number (ε_{eq}) ranging from 0 to 1 for each equipment *eq*.
    For each equipment *eq*
      If $\varepsilon_{eq} < FOR_{eq}$
        $U_{eq} = 0$ (down state - outage)
      End if
    End for
  End for
  Perform the state reduction;
  Compute the EPNS for the candidate plan using (11)–(22);
End for

3. Proposed multiobjective solution approach: MEPSO-II algorithm

3.1. Motivation

Several researchers have been proposing multiobjective versions of the EPSO and PSO as in [2,21,22] to address a wide number of power system problems. Accordingly, we adopted the term MEPSO-II (similar to what happened when NSGA was enhanced to NSGA-II) to stand for *Multi-Population and Multiobjective Evolutionary Particle Swarm Optimization.* Although the name similarity, the proposed method is an original MO extension of the EPSO algorithm and it combines characteristics and important concepts of evolutionary computation and multi agent population methods.

In this paper, the developed MEPSO-II is compared against MEPSO and NSGA-II. In this comparison, MEPSO is important because it is the first multiobjective version of EPSO and NSGA-II is used for comparison purposes in the vast majority of studies dealing with the multiobjective TEP as in [3,4,7]. The main motivations for the development of the MEPSO-II tool are detailed below:

(a) The NSGA-II [19] and the MEPSO [2] use the maximum number of iterations as stopping criterium. This does not ensure the convergence of the problem since the random parameters typical of evolutionary computation can originate the algorithms to converge to different solutions, sometimes taking much more iterations than in others. In this case, the MEPSO-II converges if a predefined number of iterations are run without observing changes in the best individual for each population. This way, we ensure that the evolutionary process converges having in mind that in multiobjective problems the concepts of *global* and *local optima* are replaced by the concept of *non dominance* already mentioned in Section 1. The relevant issue is that if a pre-defined number of iterations is used, the populations can still present a considerable diversity when the process ends and the Pareto-Front could still be improved if there were more iterations available. This means that it is not ensured that a stable Pareto-Front is obtained. Differently, stopping only if the best individual in each population is unchanged for a specified number of iterations is a far more reliable criterium to obtain a good quality and stable final solution;
(b) In MEPSO and NSGA-II the population is divided in different fronts and its evolution is obtained considering individuals selected from internal fronts taking into account the nondominated sorting and crowding distance rank concepts. This process may ensure the *dominating effect* illustrated in Fig. 1 in terms of identifying new solutions that dominate already existing ones. However, it will hardly ensure the *scattering effect* in terms of being able to enlarge the area covered by the Pareto-Front and this is important to build

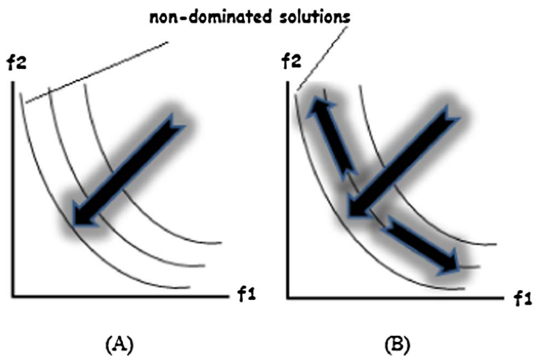

Fig. 1. The dominating (A) and the scattering (B) effects.

better quality fronts. Differently, MEPSO-II works with as many populations as the number of objectives and each one evolves towards the *gbest* (always related with the best fitness function of the corresponding population) and *pbest* (always related with the best fitness function of each individual). As the *pbest* is always in an internal front it ensures the *dominating effect* while the *scattering effect* is ensured by the *gbest* that is always located in the extreme points of the Pareto-Front;

(c) The MEPSO and the NSGA-II tools build the population for the next generation based on the less dominated individuals of the current population. However, a dominated solution may evolve to a non-dominated one in future generations if its code undergoes some change for instance when performing the mutation or replication steps. The MEPSO and NSGA-II do not allow this type of change and this may also compromise the diversity of the population. Differently, the MEPSO-II builds the populations for the next generation using an elite that includes the non-dominated solutions. The population is then completed using a tournament selection.

3.2. Pareto-front exploitation via MEPSO-II

MEPSO-II aims at exploiting in a more accurate way the non-dominated solutions in the search space. Fig. 1 illustrates the main advantage of the proposed tool over the MEPSO and the NSGA-II tools. Fig. 1(A) illustrates the improvement of the front due to the *dominating effect*, and the *scattering effect* in terms of widening the Pareto-Front is illustrated in Fig. 1(B).

The dominating effect is responsible for forcing the Pareto-Front as much as possible towards the non-dominance zone, while the scattering effect is responsible for pushing the solutions towards the extremes points of the Pareto-Front in order to enlarge its covered area. The elite set ensures the dominating effect while the movement rule considering the best population ensures the scattering effect.

Finally, the diversity of each population is ensured by the combination, at the end of each iteration, of the population's individuals through the elitism process. This procedure guarantees that the non-dominated solutions considering all parallel populations are passed to the next generation. In order to complete the populations, it is used a typical tournament selection comparing pairs of solutions. This comparison also contributes to improve that diversity.

3.3. MEPSO-II formulation

The initial populations, one per objective, are created randomly and each of them is then evaluated. After that, each population is cloned r times. The weights and the best particle found until the current iteration for each population are mutated using (23) and (24) in which the symbol $*$ represents the mutation operator. The sigmoid function in (23) is used because of its chaotic behavior and as a way to keep the self-adaptation capabilities of the swarms while at the same time controlling their amplitude variations. The use of this sigmoid function is also reported to introduce changes in the position of the particles so that in case they are trapped in a local optimum it will then be possible to more easily escape from it [6].

$$\overset{*}{w}_{ik}^{it+1} = 0.5 + rand() - \frac{1}{1 + e^{-\overset{*}{w}_{ik}^{it}}} \quad (23)$$

$$\overset{*}{gbest} = gbest + round(2 \cdot \overset{*}{w}_{i4}^{it+1} - 1) \quad (24)$$

Once the mutation step is complete, new offsprings are created for each particle in each cloned population using the EPSO movement rule and rounding up the value obtained for each position to integers [23]. The position of a particle i in iteration $it+1$ is given by (25) as a result of the addition of its position in iteration *it* with the velocity vector v that is given by (26). The communication factor P in (24) is used to control the information transmitted by the particles about the collective knowledge inside the swarm [24].

$$x_i^{it+1} = x_i^{it} + v_i^{it+1} \quad (25)$$

$$v_i^{it+1} = \overset{*}{w}_{i1}^{it+1} \cdot v_i^{it} + \overset{*}{w}_{i2}^{it+1} \cdot (pbest_i - x_i^{it}) + \overset{*}{w}_{i3}^{it+1} \cdot (gbest - x_i^{it}) \cdot P \quad (26)$$

In order to characterize each solution, it is obtained the associated investment cost and the corresponding operational cost. Thus, given a solution, that is an individual in one population, its feasibility is analysed running an AC-OPF for the expected annual peak demand. If this solution is feasible, i.e., it meets the peak demand without presenting any violations of the system constraints, the operational cost and the EPNS are calculated. Otherwise, a penalty factor is considered for the operational cost. In this case, in order to save computation time, the EPNS is not estimated and the evaluation function of this solution is just penalized to ensure that it is eliminated along the evolution process.

Finally, all individuals of all populations are ranked and sorted based on the concept of dominance mentioned in Section 1. The non-dominated solutions are included in the set termed as elite and the elements in this set are always included in all populations. After that, the populations are completed through a tournament selection process. In this step, recall that we have *r* clones for each population each of them having *ps* particles. The elitist process works separately for each population. It takes the first particle of each of the *r* clones, compares the *r* particles and it survives the one that has the best fitness function. This procedure is repeated for all *ps* particles so that at the end a new population is created having the same size of the initial one and the values of *gbest* and *pbest* are updated. This iterative process ends when the *gbest* in all populations does not change after running a pre-specified number of iterations. The pseudo-code for a general MEPSO-II application is provided below.

Pseudo-Code 2 (*MEPSOII Algorithm*).

Set the number of populations equals to the number of objectives;
Set the fitness function of each population as the respective objective
While stop criteria is not satisfied
  For each population
    Replication block – Clone each population r times
    Mutation block – Eq. (23) and Eq. (24)
    Recombination block – Eq. (25) and (26)
    Evaluation block – Evaluate each particle in each population, using its own fitness function
    Selection block – Elite (non-dominated solutions of all populations) + Tournament selection (to complete all the populations with *ps* particles).
  End for
End while

4. Performance evaluation

There are several Multiobjective Evolutionary Algorithms, MOEAs, described in the literature, which means that their comparison and performance evaluation is a relevant issue. This evaluation is usually based on the comparison of the Pareto-Front built by the approach under analysis with the real Pareto-Front of the problem, admitting that this true front is available from another method. In a similar way to the approach adopted in [2], this comparison requires determining a suitable Pareto-Front beforehand. Although the true Pareto-Front is usually not available, the solutions obtained from running several multiobjective tools are combined to estimate the true front. In this sense, [25] details a number of metrics to assist this performance evaluation, although it is clear that no single metric is able to fully evaluate all the capabilities of a MOEA and therefore they should be carefully used especially when interpreting the results. Finally, the performance evaluation used in this work has the main objective of assessing the quality of the Pareto-Front built by the proposed algorithm and also by the NSGA-II and the MEPSO regarding the accuracy, the spread and the distribution of the solutions. The next paragraphs detail the four metrics that were used for this purpose.

Error Ratio (ER) - This metric returns the percentage of solutions in the calculated Pareto-Front (PF_{know}) which do not belong to the real Pareto-Front (F_{true}) and it is given by (27). This metric can be used to evaluate the accuracy of the PF_{know} in discrete search spaces. In (27) *npf* is the number of solutions in PF_{know} and e_i is zero if solution *i* belongs to PF_{true} and it is one otherwise.

$$ER = \sum_{i=1}^{npf} \frac{e_i}{npf} \tag{27}$$

General Distance (GD) - This metric indicates how far PF_{know} is from PF_{true}. It is given by (28) in which *ed* represents the Euclidean distance between each solution in PF_{know} to each solution from PF_{true} .

$$GD = \frac{\sqrt{\sum_{i=1}^{npf} ed_i^2}}{npf} \tag{28}$$

Pareto-Front Ratio (PFR) - This metric corresponds to the percentage of points in the calculated Pareto Front that are in the true front and it is given by (29).

$$PFR = \frac{|PF_{know} \cap PF_{true}|}{|PF_{true}|} \tag{29}$$

Relative Spacing (S) - This metric is used to measure the spread and the distribution of the solutions throughout PF_{know} and it assesses how well PF_{know} is distributed. This metric is given by (30) and (31) in which D_i is the relative distance between consecutive solutions (i = 1, …, *npf*) and *Dm* is the mean of all D_i.

$$D_i = \frac{OF_1^i - OF_1^j}{OF_1^i} + \frac{OF_2^i - OF_2^j}{OF_2^i}, \quad \forall\, i,j \in PF_{know} \wedge j = i + 1 \tag{30}$$

$$S = \sqrt{\frac{1}{npf-1} \cdot \sum_{i=1}^{npf} (Dm - D_i)} \tag{31}$$

5. Numerical simulations

5.1. Outline of the tests

This section presents the results obtained by the proposed MEPSO-II tool and the performance evaluation when compared to MEPSO and NSGA-II. These tools are often used in power system analysis and they are reported to perform very well in obtaining the Pareto-Front of multiobjective problems. The NSGA-II used in this paper is identical to the one presented in [19] and the MEPSO corresponds to the approach described in [2]. The parameters used for the NSGA-II and MEPSO are the same as used for the MEPSO-II but using 50 generations as the stop criterion.

As evolutionary computation may output different solutions for multiple runs and may display convergence problems, we ran the MEPSO-II ten times using the *IEEE 24 bus Reliability Test System* in order to access the efficiency of the proposed approach. On the other hand, as TEP problems present a non-linear and non-convex nature that can lead to a prohibitive computational effort, the *Midwest 118-bus American Electric Power System* was used in order to check the scalability of the proposed method. In this case, the evaluation was done just running the problem once.

As the number of AC-OPFs required to estimate the PNS and EPNS values is large, in this paper we used the interior point method available in the solver [26] to solve the mentioned OPF problems. Besides, to reduce the computational burden required by these calculations, all the simulations were run using parallel computing in MATLAB on an Intel i7, 3.4 GHz, 16 GB RAM.

Finally, it is important to note that the TEP literature reports results for models using different objectives and different versions of the test systems. This lack of uniformity means that the literature does not provide results to immediately compare existing approaches with MEPSO-II. This difficulty was the main motivation to conduct the comparative analysis that we are now reporting.

5.2. General data

All the tests were done using a 10-years planning horizon. The simulations were performed using a penalization factor for PNS equal to 10^9 \$/MW and after some trial runs the number of particles in the two populations was set at 40 particles because this was a good compromise between the quality of the results and the calculation time. We used a discount rate of 5% and a load growth of 2.5% per year in line with typical values used in recent years for power system simulations although this does not represent any constraint for the model and different values can easily be tested. For both test systems, the forced outage rate of generating units is set at 4% and for cables, transformers and transmission lines we used 1%, the commissioning time is considered 1 year for all equipments in both test systems. Although these values are very often used in the literature, it is clear that if another network is analysed different values will eventually have to be used. The loads of both test systems are modeled as negative real power injections with associated negative costs as described in [26].

Table 1 includes the values of the annual peak demand for these two test systems and Table 2 gives the list of the candidate equipment for the two systems. This list includes overhead lines, cables and transformers as these are the most typical components in TEP formulations. However, this list can include other elements as var devices, provided that for each possible element we specify its connection bus and investment cost. Although, using parallel computation reduces the computational burden, the numerical simulations were time consuming because there are 10^{21} combinations of equipment to perform the expansion for each system given the number of elements in the list of candidates and the number of periods in the horizon.

5.3. Results or the IEEE RTS 24 Bus - 10 runs

The topology and data of the IEEE 24 Bus RTS is available in [27]. Regarding the original values in [27], the values of all loads were duplicated and the installed capacity of all generators were tripled (real and reactive) in order to turn the network more stressed.

In order to analyze the convergence behavior of the MEPSO-II tool, we solved the TEP problem setting the stop criterion in six different thresholds as 5, 10, 15, 20, 25 and 30 iterations with the same *gbest* for the two parallel populations. The Error Ratio and the computation time for each threshold used in the MEPSO-II tool are presented in Fig. 2.

Table 1
Annual peak load forecast.

Year	1	2	3	4	5	6	7	8	9	10
RTS 24 Bus (MW)	5700.00	5842.50	5988.56	6138.27	6291.73	6449.02	6610.25	6775.51	6944.89	7118.52
118 Bus (MW)	6363.00	6522.07	6685.12	6852.25	7023.56	7199.15	7379.13	7563.60	7752.70	7946.51

Table 2
Candidate equipment.

Candidate	RTS 24 Bus Test System				118 Bus Test System			
	Equipment	From	To	Cost (10^3 S$)	Equipment	From	To	Cost (10^3 US$)
1	138 kV line	1	3	55.00	138 kV line	5	6	54.00
2	138 kV line	2	6	50.00	345 kV line	9	10	161.00
3	138 kV line	2	6	50.00	345 kV line	8	30	50.40
4	138 kV line	2	6	50.00	345 kV line	8	30	50.40
5	138 kV line	8	10	43.00	138 kV line	49	51	137.00
6	138 kV cable	6	10	16.00	138 kV line	59	61	150.00
7	230 kV line	12	13	66.00	138 kV line	47	69	277.80
8	230 kV line	14	16	54.00	138 kV line	69	77	101.00
9	230 kV line	14	16	54.00	138 kV line	77	78	12.40
10	Transformer	3	24	50.00	138 kV line	79	80	70.40
11	138 kV line	7	8	16.00	138 kV line	94	100	58.00
12	138 kV line	7	8	16.00	138 kV line	110	111	75.50
13	Transformer	9	12	50.00	345 kV line	30	38	54.00
14	Transformer	9	11	50.00	138 kV line	94	95	43.40
15	Transformer	10	11	50.00	138 kV line	17	113	30.10
16	Transformer	10	12	50.00	138 kV line	23	32	151.30
17	138 kV line	1	5	22.00	345 kV line	8	9	152.50
18	138 kV line	2	4	33.00	138 kV line	82	83	36.65
19	230 kV line	20	23	30.00	138 kV line	37	39	106.00
20	230 kV line	17	18	20.00	Transformer	68	116	20.25

According to these results, if the convergence criterion is set at 5 iterations with the same best individual for each population, the Error Ratio of the Pareto-Front is 30% with a computation time around 37 min. On the other hand, setting the convergence criterion in 30 iterations, the Error Ratio becomes null, but this requires a time about 5.5 times bigger. These results confirm one of the contributions of the proposed tool, that is, a better control of the solution convergence, as mentioned in Section 3.

In order to further analyze the convergence and the efficiency of the construction of the Pareto-Front, we ran the TEP problem ten times using the 24-Bus Test System. In this case, the convergence criterion was set in terms of running 10 iterations with the same *gbest* for the two parallel populations. The Pareto-Fronts built by the proposed MEPSO-II tool as well as by the MEPSO and NSGA-II tools are displayed in Fig. 3 for each of these ten simulations.

If a larger number of iterations with the same best individual was required for convergence, the computational time would increase taking into account that for the 24-Bus Test System we ran the problem 10 times. However, if a larger number of iterations was used, the results would be even more favorable to the MEPSO-II, as the Pareto Front provided by the MEPSO-II is generally closer to the real one.

Although in simulations 5 and 9 displayed in Fig. 3, MEPSO-II presented worse results than those obtained by the MEPSO and NSGA-II, the proposed model provides a smaller Error Ratio, a smaller General Distance, a larger Pareto-Front Ratio and a better distribution of solutions over the front when compared to the Pareto Fronts built by these two alternative tools over the ten simulations. The performance of the three analysed tools in terms of ER, GD, PFR and S over the ten simulation runs is provided in Fig. 4.

5.4. Results for the single run using the IEEE 118 Bus system

The data for the IEEE 118-Bus Test System is provided in [26] in *case118* file. Fig. 5 presents the Pareto-Front obtained by the proposed toll as well as the Pareto-Fronts built by MEPSO and NSGA-II. Table 3 presents the metrics to compare the three analysed tools applied to 118 Bus Test System.

Similar to the results reported in Section 5.3, the MEPSO-II presents a better performance regarding these metrics, which means that it has a far larger percentage of points in the true Pareto-Front, a shorter distance to the true Pareto-Front and a smaller error to build the Pareto-Front when compared to the results provided by the other two MO tools. In order to build the Pareto- Fronts, the MEPSO-II requires more time than the other two tested tools, but TEP is recognized as an off-line study which means that taking more time to get better quality results can be seen as an affordable trade off.

6. Discussion and conclusions

The changes experienced by power systems over the last years turned very complex the development of simulation tools to address long term planning problems. However, long term planning is still an important activity namely as a way to ensure on the long term the safe and secure supply of the demand. In line with these concerns, this paper presents a new tool that is able to deal with the multiobjective nature of the transmission expansion planning problems while providing better quality results when compared with other tools.

The novel MEPSO-II tool uses parallel populations to exploit in a better way the non-dominated solutions through the dominating and the scattering effects. These effects enabled the development of a robust mechanism to build the Pareto Front as it was illustrated by comparing the results provided by MEPSO-II with the ones from two well-disseminated and consolidated tools described in the literature: the MEPSO and the NSGA-II. The results are compared using the statistical metrics Error Ratio, General Distance, Pareto-Front Ratio and Relative Spacing detailed in Fig. 4 and Table 3 for the two tested systems, and

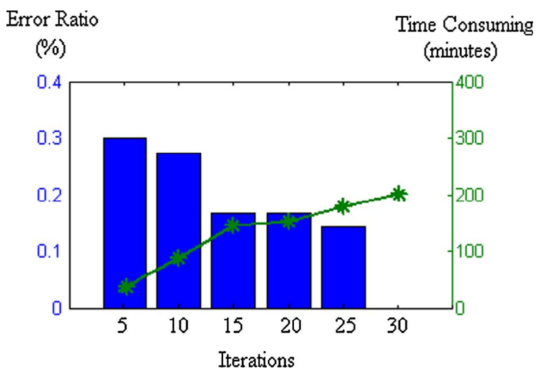

Fig. 2. Error ratio and computation time for the IEEE 24 Bus Test System.

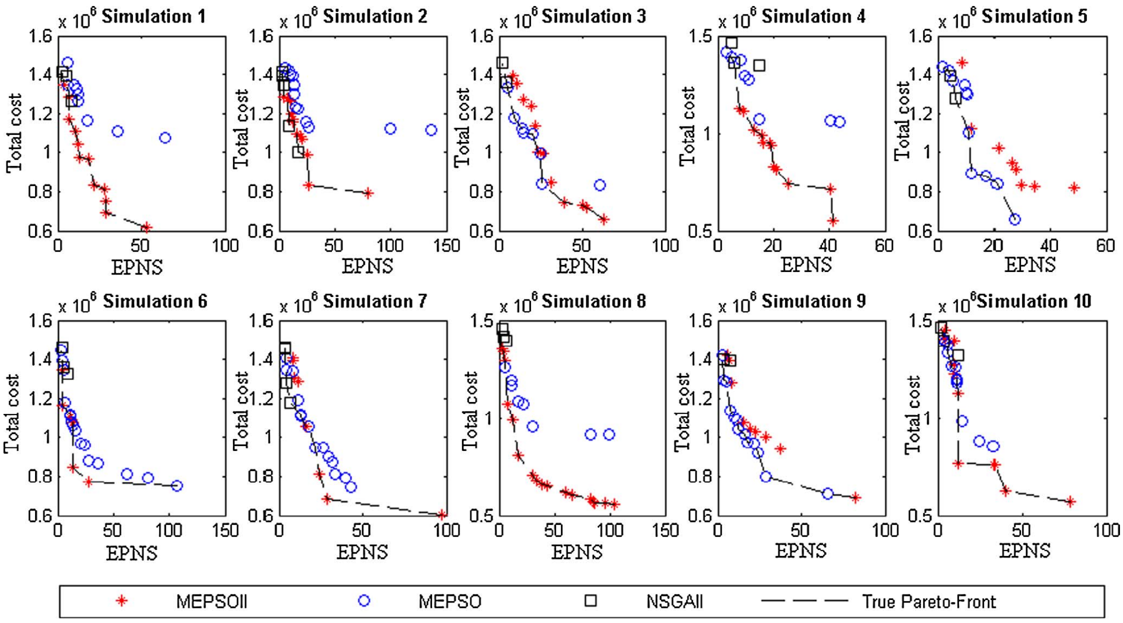

Fig. 3. Pareto-Fronts from 10 runs for MEPSO-II, MEPSO and NSGA-II - IEEE 24 Bus Test System.

this comparison is very favorable to the MEPSO-II both regarding the IEEE 24 Bus and the IEEE 118 Bus Test Systems.

The developed approach was applied to the TEP problem considering the minimization of the system total costs that comprises investment costs and the operation costs while considering also the minimization of the expected power not supplied, which is estimated taking into account the uncertain behavior associated with the lifetime of system components using the respective FORs. The developed MEPSO-II tool can be easily adapted to consider demand and generation uncertainties, in this case associated to hydro, wind or solar resources. This would require specifying probabilistic distributions for these variables and sampling values for each of them to be used in the evaluation block of the MEPSO-II algorithm. All these characteristics together with the performance of the MEPSO-II algorithm can be used by transmission providers in a fruit full way to build more robust long-term investment plans.

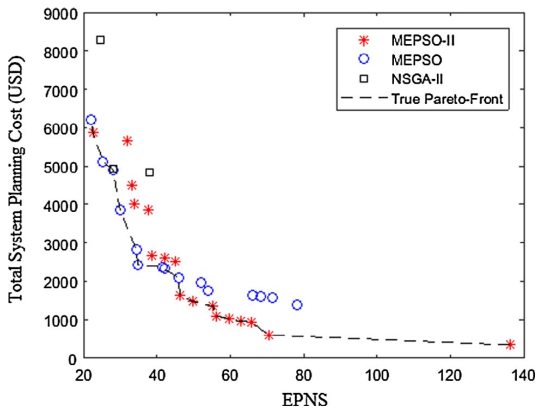

Fig. 5. MEPSO-II, MEPSO, NSGA-II and True Pareto-Fronts for the 118 Bus Test System.

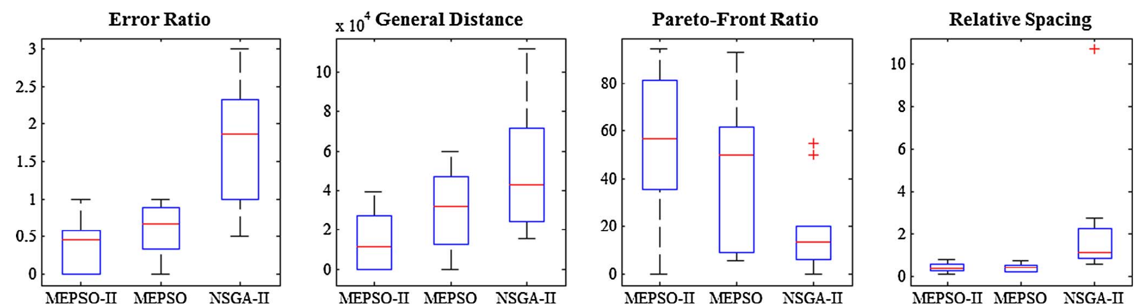

Fig. 4. Detailed performance for MEPSO-II, MEPSO and NSGA-II using the IEEE 24 Bus Test System for 10 runs.

Table 3
Metrics from MEPSO-II, MEPSSO and NSGA-II.

	MEPSO-II	MEPSO	NSGA-II
ER	0.4118	0.5333	3.3333
GD	$0.1332 \cdot 10^3$	$0.0660 \cdot 10^3$	$1.1957 \cdot 10^3$
PFR	50	45	5
S	0.3043	0.3232	0.8763

Acknowledgements

This work was supported in part by the Coordination for the Improvement of Higher Education Personnel (CAPES, Brazil) under Grant 13207-13-0.

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B.0.10 Technical-economic analysis for the integration of PV systems in Brazil considering policy and regulatory issues. (Energy Policy, 2018)

Energy Policy 115 (2018) 199–206

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Technical-economic analysis for the integration of PV systems in Brazil considering policy and regulatory issues

P. Vilaça Gomes[a,b,*], N. Knak Neto[a,c], L. Carvalho[a], J. Sumaili[a], J.T. Saraiva[a,b], B.H. Dias[d], V. Miranda[a,b], S.M. Souza[a,e]

[a] Institute for Systems and Computer Engineering, Technology and Science – INESC TEC, Portugal
[b] Faculty of Engineering – University of Porto, Portugal
[c] Universidade Regional Integrada do Alto Uruguai e das Missões, Brazil
[d] Federal University of Juiz de Fora, Brazil
[e] Eletrobras, Brazil

ARTICLE INFO

Keywords:
PV systems
Brazil
Net metering
Distributed generation
Economic analysis
PV systems penetration

ABSTRACT

The increasing integration of distributed renewable energy sources, such as photovoltaic (PV) systems, requires adequate regulatory schemes in order to reach economic sustainability. Incentives such as Feed-in Tariffs and Net Metering are seen as key policies to achieve this objective. While the Feed-in Tariff scheme has been widely applied in the past, it has now become less justified mainly due to the sharp decline of the PV system costs. Consequently, the Net Metering scheme is being adopted in several countries, such as Brazil, where it has is in force since 2012. In this context, this paper aims to estimate the minimum monthly residential demand for prosumers located in the different distribution concession areas in the interconnected Brazilian system that ensures the economic viability of the installation of PV systems. In addition, the potential penetration of PV-based distributed generation (DG) in residential buildings is also estimated. This study was conducted for the entire Brazilian interconnected system and it demonstrates that the integration of distributed PV systems is technical-economic feasible in several regions of the country reinforcing the role of the distributed solar energy in the diversification of Brazilian electricity matrix.

1. Introduction

1.1. Motivation

The current scenario of electricity in Brazil reached alarming levels due to its growing cost and the permanent risk of having Energy Not Supplied (ENS). Among the reasons that are contributing to this crisis the following ones can be mentioned:

- low tariffs determined during a long period by the National Regulatory Agency for Electricity (ANEEL) led the distribution companies (DisCo) to operate in financial deficit, resulting in many of them being rescued by the national treasury;
- the constant delays in the implementation of new power generation and transmission line projects;
- a high number of energy auctions, resulting in low price of energy, which prevented achieving the return rates required by the market;
- the hydric shortage had a major impact on the security of supply since the hydropower account for about 70% of Brazil's energy mix.

Therefore, the mentioned alarming scenario and the strong hydraulic dependence of the Brazilian energy mix in combination with the increasing electricity demand and the constant concern with the preservation of the environment are driving the Brazilian scientific community to look forward to exploring other renewable energy sources, such as solar. On this regard, Brazil has a large solar energy potential due to an advantageous geographical location, with most of its area in inter-tropical regions and a global incident solar radiation between 1900 and 2150 kWh/m^2 throughout the year (SolarGIS, 2017). These values are larger than in most European Union countries, such as Germany, France and Spain, where solar energy projects (some of which strongly relying on government incentives) are widely disseminated (Miranda et al., 2015).

The exploitation of energy generation from renewable sources has been increasing in several countries, in most cases induced by regulatory incentives for small distributed generation (DG) such as Feed-in Tariffs and Net Metering schemes (del Río and Mir-Artigues, 2012; Jacobsson and Lauber, 2006). These incentives are justified by the potential benefits that DGs can provide to the electrical system, namely

* Corresponding author at: Institute for Systems and Computer Engineering, Technology and Science – INESC TEC, Portugal.
E-mail address: phillipe.gomes@fe.up.pt (P. Vilaça Gomes).

https://doi.org/10.1016/j.enpol.2018.01.014
Received 9 October 2017; Received in revised form 2 January 2018; Accepted 7 January 2018
Available online 28 January 2018
0301-4215/

the postponement of investments in the expansion of generation, transmission and distribution systems, the reduction of the environmental impacts, the reduction of the electricity demand levels, the reduction of active power losses, and the diversification of energy sources (Maciel et al., 2012). The Net Metering scheme, which is in force in Brazil since 2012, was the first strategy presented by the National Electricity Agency (ANEEL) to reduce barriers for the integration of small-scale distributed power plants based on renewable energies, such as PV systems.

1.2. Literature review

Several studies have been conducted concerning the economic viability of PV DG in Brazil based on the Net Metering regulation. In this scope, reference (Pereira et al., 2012) describes the current status in 2012 and the potential for the renewables in Brazil. Several scenarios for PV technology deployment in Brazil in the year 2030 are studied in (Jannuzzi and de Melo, 2013) considering policy mechanisms aiming at promoting the development of PV generation connected to distribution networks. Besides, an evaluation of the market penetration potential in each case using a logit-function approach was done and the results show that PV systems have good opportunities for Brazil to diversify its energy matrix while increasing the potential economic and environmental benefits. In (Lacchini and Dos Santos, 2013), the authors analyze the evolution of the integration of PV systems by comparing their total costs with coal-fired generation, furthermore, some government incentives are proposed to narrow the existing financial gap between these two technologies.

In (Dávi et al., 2016; Holdermann et al., 2014; Lacchini and Rüther, 2015) it is described an economic viability analysis of a PV system for the residential and commercial sectors after the introduction of the net metering regulation. In this study the current electricity tariffs are used as well as some fees and taxes, however the cost of electricity availability is not considered. The research reported in (Rodrigues et al., 2016) presents an economic analysis for PV systems all over the world, by comparing the policies adopted in Australia, Brazil, China, Germany, India, Iran, Italy, Japan, Portugal, South Africa, Spain, the UK and the USA in order to assess which of these countries have the most attractive policies to induce investments in PV systems. The work in (Pinto et al., 2016) uses the Brazilian solar irradiations levels in order to calculate how many PV panels are necessary to supply the average electricity demand of social housing programs and the results confirm that PV panels are an important alternative for the Brazilian energy crisis.

Finally, (de Faria et al., 2017) highlights the challenges and prospects for the PV systems on Brazilian DG describing some incentives implemented to date in order to develop the solar electricity generation. These authors were motivated by the increase participation of alternative renewable sources as wind and small hydro (while solar energy utilization is underutilized) in the electricity market, induced by mechanisms designed to stimulate its implementation as the Net Metering regulation by the normative resolution 482.

On the other hand, references (Camilo et al., 2017; Vale et al., 2017) report case studies for the PV system integration in Brazilian households considering financial and technical effects in the low voltage systems. The results prove that further regulating and market efforts are required to expand the solar generation by residential consumers.

1.3. Contribution and structure

In this study, the minimum monthly residential demand to ensure the economic viability for PV systems – the *threshold demand* – is computed for prosumers located in all distribution concession areas in Brazil. Furthermore, the potential penetration of PV systems for residential consumer is also estimated for each Brazilian region. The methodology that was adopted in this work is unprecedented in the literature in the sense that it takes into account not only the Net Metering regulation but also the Agreement 16 and the Normative Resolution 414 introduced by the Brazilian government to promote DG and specifying the general conditions of electric power supply, respectively. While these agreements and regulations are widely used by the electric industry, they were never considered in this type of study.

Regarding the structure of the paper, Section 2 presents the main strategies adopted by the government to encourage the penetration of DGs, Section 3 describes the methodology used in this study, Section 4 reports the main results and, finally, Section 5 includes the comments and conclusions that can be drawn from this work.

2. Government legislation on the Brazilian DG

2.1. The normative resolution 482 (RN482)

In April 2012, ANEEL introduced the Net Metering mechanism through the RN482 in order to reduce barriers to the connection of small renewable-based power plants to distribution networks. Net Metering is an incentive mechanism for DGs, in which an elective consumer, properly connected to a distribution network, can inject to this network the surplus energy for later use. This mechanism allows two-way energy traffic between DG and the distribution network and consequently the network can be seen as playing the role of storing energy.

However, in April 2015, i.e. three years after this normative resolution was passed, there were only 478 PV systems installed in Brazil, which led to an update of this regulation in November 2015 (ANEEL, 2015), namely addressing the limits of the installed capacity and the compensation schemes. Currently, the normative defines micro DG as an electricity generation plant with installed capacity less than or equal to 75 kW and mini DG as a unit with installed power larger than 75 kW and less than or equal to 5 MW (3 MW for hydraulic sources). In addition, the RN482 sets a compensation scheme by granting a credit to the consumers that can be used by up to 60 months if the amount of energy injected in the network is larger than the local consumption. This compensation scheme corresponds to a major change introduced by the RN482 regarding PV systems because it means that any economic analysis should take into account the monthly energy balance over the horizon plan.

2.2. The agreement 16

There are several taxes that are applied to the electric energy produced by DGs. Among those, the Goods and Services Tax (ICMS) is the most expressive one. This tax is independently established by each of the 27 Federal Units of Brazil (26 States plus the Federal District). The rates vary from 0% to 30% and there are two different ways to apply it to the electricity bill. In the first case, the base for the calculation of the ICMS is the electricity supplied by the network to the consumer whereas, in the second case, the tax is applied to the electricity balance, i.e., the difference between the electricity injected and the electricity supplied by the network.

In April 2015, the National Finance Policy Council (CONFAZ) published the Agreement 16 that authorized some states to apply the ICMS on the electricity balance (CONFAZ, 2015). In August 2017 twenty-one Federal Units have signed the agreement, namely, Pará, Acre, Alagoas, Bahia, Ceará, Goiás, Maranhão, Mato Grosso, Minas Gerais, Paraíba, Pernambuco, Piauí, Rio de Janeiro, Rio Grande do Norte, Rio Grande do Sul, Rondônia, Roraima, São Paulo, Sergipe, Tocantins, and the Federal District of Brasília. The Federal Units that did not sign this agreement are: Amazonas, Amapá, Espirito Santo, Mato Grosso do Sul, Paraná and Santa Catarina.

Government subsidies and strategies are extremely important to boost the penetration of PV systems in the distribution network (Silveira et al., 2013), which means that it is clear that an adequate incentive structure for PV systems will very much favor its penetration

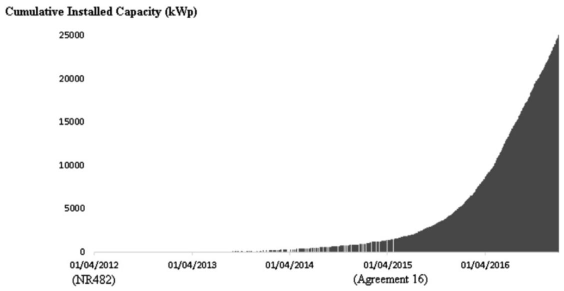

Fig. 1. Cumulative PV penetration on Brazil for residential consumers (kWp is related to peak) (ANEEL, 2017a).

as depicted in Fig. 1. This Figure shows the evolution of the penetration of PV systems in residential consumers in Brazil. Note that the PV DG penetration in the residential market, which was barely noticeable after the RN482 in 2012, was significantly boosted by the Agreement 16 in 2015.

2.3. The normative resolution 414 (RN414)

The RN414 introduces the cost of electricity availability (ANEEL, 2010) which expresses the amount paid by the residential consumers to the DisCos to guarantee the availability of electric energy supply even if it is not used. This financial compensation varies according to the way that the residential consumer is connected to the network: for single-phase network connections, this cost is equivalent to the consumption of 30 kWh; for two-phase connections, it is equivalent to 50 kWh; for three-phase connections, it is equivalent to 100 kWh (ANEEL, 2010).

The RN414 has a stronger impact in the cash flow of the PV system investment as well as in its size. Bearing in mind that the consumer must pay the cost of electricity availability every month, the PV system should not be sized to supply the entire monthly residential demand but this demand discounted by the demand that is equivalent to the cost of electricity availability. If this procedure is not followed, then the equivalent demand will be supplied twice: from the distribution network and from the PV system.

3. Developed methodology

The main goal of this study is to determine the minimum residential monthly electricity consumption in each DisCo of the Brazilian interconnected system to make the PV system investment economically feasible. This minimum electricity consumption – called *threshold demand* – is an important parameter for the residential prosumers and for the DisCos. In fact, it can be used not only to determine the payback period for the investment in the PV system but also to anticipate the impacts of PV generation on the distribution system so that adequate expansion plans can be developed in due time. As a second objective, this paper aims at providing a comprehensive techno-economic assessment for the potential PV penetration in each Brazilian region based on the mentioned threshold demand.

The procedure adopted to compute the threshold demand for a predefined DisCo requires the determination of the residential monthly electricity consumption that makes the levelized cost of energy (LCOE) associated to the PV system at least equal to the current electricity tariff in that DisCo. Therefore, when the LCOE associated to the PV system becomes equal to the current electricity tariff, then the investor feels indifferent between investing in the PV system or continuing to be supplied by the main network, which means that grid parity was reached (Bhandari and Stadler, 2009).

The threshold demand was computed for all the 63 DisCos that exist in the interconnected Brazilian system. Fig. 2 illustrates the steps of the iterative optimization process that is used to obtain the threshold demand for each DisCo and the corresponding PV penetration. Briefly, the process starts by setting the residential demand (d_i) at 1 kWh larger than the equivalent demand of the cost of electricity availability (d_{cea}). Then the PV system is sized to meet the *applicable demand* (introduced in Section 3.1) considering the real and local characteristics of solar irradiation, the normative resolutions 414 and 482 and the panel parameters. Using these elements, the monthly energy balance is calculated taking into account the RN482 and the Agreement 16 in order to compute the cash flow. Subsequently, the cash flow considering the RN414 is obtained for the entire planning horizon to compute the correspondent LCOE. This process is repeated by increasing the monthly residential demand by 1 kWh in each iteration until the maximum monthly residential demand is reached. Finally, when the LCOE associated with the monthly residential demand reaches the current tariff, the grid parity is obtained and this demand is termed as the threshold demand. Then, using the mentioned threshold demand for each DisCo, the potential PV penetration can be estimated by inferring the number of residential consumers with a monthly electricity consumption above that value. This final analysis is built upon the report published by the Energy Research Office (EPE) (EPE, 2014).

The computation of the threshold demand can result in two different outcomes. In order to illustrate these possible outcomes, let us consider two DisCos, DisCo 1 and DisCo 2, and the graphs in Fig. 3. Regarding DisCo 2 the residential demand is increased along the iterative process and the LCOE of the respective PV system becomes equal to the corresponding current electricity tariff of DisCo 2 (grid parity), clearly leading to the threshold demand. However, for DisCo 1 the residential demand is changed over the iterations but the respective LCOE for the investment in the PV system never becomes equal to the current electricity tariff of the DisCo 1. In this second situation, the PV system is economically unfeasible for the residential customers supplied by DisCo 1. Note that, in this case, the threshold demand cannot be obtained for the range of demand considered mainly because the current tariff of this DisCo is very reduced so that it is more reasonable from an economic point of view to continue being supplied by the network.

3.1. PV system sizing

The monthly energy balance is obtained from the bidirectional balance between the distribution network and the PV generation system. The monthly cash flows are computed based on the RN482 that states that the electricity credit can be compensated in up to 60 months.

As mentioned before, the Brazilian DisCos should receive a payment from the availability of the electricity supply, even if the electricity balance is positive or zero. Accordingly, the residential demand used to size the PV system for the geographical area of DisCo i – termed *applicable demand* – corresponds to the difference between the residential demand and the equivalent demand associated to the cost of electricity availability as indicated in Eq. (1).

$$d_{apl} = d_i - d_{cea} \tag{1}$$

As it was already mentioned, this is the most economical way to size the PV system in the case of Brazilian distributed generation. If the PV system is sized for the residential demand d_i, then the initial investment would increase but the payments related to the d_{cea} remain unchanged, i.e. the PV system becomes oversized.

Therefore, the PV system investor will have its electrical demand (d_i) supplied in part by the PV system (d_{apl}) and in part by the distribution network (d_{cea}). The inclusion of d_{cea} is essential to avoid oversizing the PV system since the cost of availability must always be payed to the DisCo.

In this study, we use the relationship between the applicable demand (d_{apl}) and the electricity generated by one PV module ($M1$) to size the number of modules (Chandel et al., 2014) (see Eq. (2), Eq. (3) and

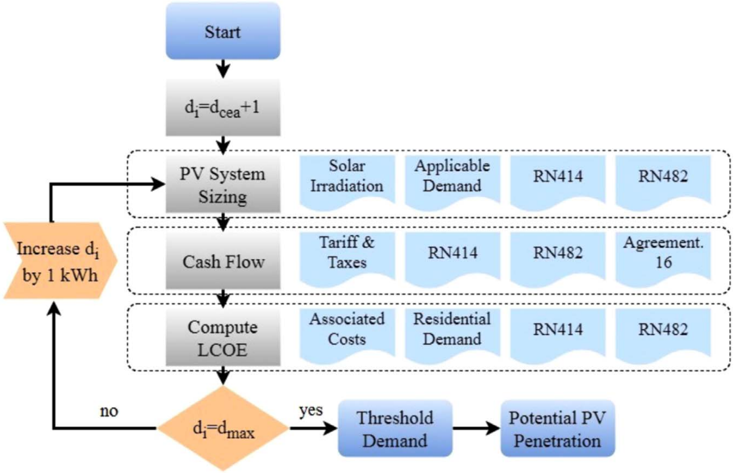

Fig. 2. Flowchart of the proposed methodology.

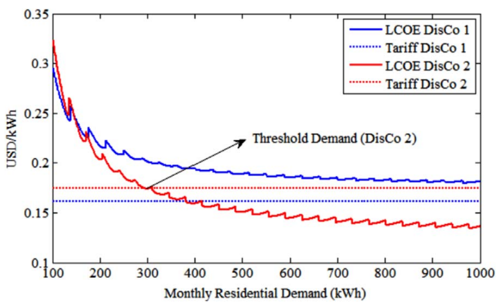

Fig. 3. Illustration of the possible outcome of the threshold demand computation.

Table 1
Parameters used to size the PV system.

M1	Monthly electricity generated by one PV module (kWh)
SI	Solar irradiation (kwh/m^2/day)
A_p	Panel area (m^2)
η	Conversion efficiency (%)
PR	Performing rate (%)
SP	Number of PV modules
ceil(x)	Function that rounds the real number *x* to the first integer that is larger than or equal to *x*
NP	Nominal power of each PV module
C_{PU}	Cost per peak unit (USD/kWp)

Table 1). Using SP, then the initial investment on the PV system is given by (4).

$$M1 = 30.\ SI.\ A_p.\ \eta.\ PR \tag{2}$$

$$SP = ceil(d_{apl}/M1) \tag{3}$$

$$I_o = SP.\ N_P.\ C_{PU} \tag{4}$$

3.2. Mathematical formulation

This study is focused only on residential customers connected to low voltage networks (< 2.3 kV). The threshold demand is calculated estimating the cash flows during the system lifetime considering the initial investment cost, the maintenance costs and the and payments made to the DisCo due to the access charges and the equivalent demand associated to the cost of electricity availability during the period of analysis. The goal of the associated optimization problem is to find the minimum monthly residential demand that makes the PV system economically feasible. Accordingly, the PV system is sized and the energy balance for the entire system planning horizon is calculated based on the electrical demand in each DisCo and its geographic location. Therefore, the cash flow for this period is calculated considering the costs, the RN482, the Agreement 16 and the cost of electricity availability introduced by the RN414. The residential demand is changed during the iterative optimization process, and based on the current value for the residential demand, the PV system is sized, the energy balance is estimated, and the LCOE is obtained. This process is repeated for each DisCo, and the

Table 2
Mathematical formulation parameters.

LCOE	Levelized cost of energy	*T*	Electricity tariff (USD/kWh)
NPV	Net present value for the PV system investment (USD)	d_{cea}	Equivalent demand to the cost of electricity availability (kWh)
Eres	Expected electricity required over the PV system lifetime (kWh)	E_{req}	Electricity required from the network (kWh)
d_i	Electricity demand under study (d_{cea}+1 to d_{max})	Ω_1	Set of Federal Units that have not signed Agreement 16
C	Associated cost due the PV system (USD)	Ω_2	Set of Federal Units that have signed Agreement 16
I	Investment cost due the PV system (USD)	G_{pv}	PV generation (kWh)
M	Maintenance cost due the PV system (USD)	G_1	PV generation in the month 1
F	DisCo payments due network usage (USD)	δ	Monthly efficiency loss (%)
γ	Value for network usage in the net metering scheme (USD)	*r*	Discount rate (%)
BCT	Basis for tax calculation	I_o	Initial investment (USD)
ICMS	Goods and Services Tax	*nt*	PV system lifetime (in months)
PIS	Tax relating to the social integration program	*t*	Index for month
EB	Electricity balance (kWh)	*i*	Index for DisCo 1–63)
β	Monthly electricity tariff rate	*j*	Index for Federal Unit 1–27)

Table 3
Number of residential costumer by electricity consumption range.

Region	Residential consumers (millions) by monthly consumption range (kWh)					
	0–100	101–200	201–300	301–400	401–500	501–1000
Midwest	1,78	1,85	0,77	0,29	0,13	0,18
South	2,95	3,51	1,74	0,63	0,26	0,30
Southeast	11,04	7,80	9,14	1,27	0,51	0,62
North	1,91	1,05	0,46	0,20	0,12	0,24
Northeast	12,99	3,25	0,86	0,27	0,14	0,22

LCOE of each PV system is calculated using (5) to (13) and Table 2 details the parameters of this formulation. In this formulation, we are assuming that the electricity generated by the PV system and the residential demand are positive numbers and the electricity required from the network is the difference between these two values. If the electricity from the PV system is larger than the residential demand, then the difference is positive and there is electricity injected in the network. On the contrary, the difference is negative and there is electricity taken from the network.

$$LCOE_{i,j,d_i} = \frac{NPV_{i,j,d_i}}{Eres_{d_i}} \tag{5}$$

$$NPV_{i,j,d_i} = \sum_{t=0}^{nt} \frac{C_{t,i,j,d_i}}{(1+r)^t} \tag{6}$$

$$C_{t,i,j,d_i} = I_{t,i,j,d_i} + M_{t,i,j,d_i} + f_{t,i,j,d_i} \tag{7}$$

$$f_{t,i,j,d_i} = \gamma_{t,i,j,d_i} + BCT_{t,j}.\left(\frac{1}{(1-ICMS_{j,d_i}).\,(1-PIS)} - 1\right) \tag{8}$$

$$\gamma_{t,i,j,d_i} = \begin{cases} |EB_{t,j,d_i}|.\,(1+\beta)^t.\,T,\ if EB_{t,j,d_i} \le -d_{cea} \\ d_{cea}.\,(1+\beta)^t.\,T,\ otherwise \end{cases} \tag{9}$$

$$BCT_{t,j} = \begin{cases} E_{req,t},\ \forall\, j \in \Omega_1 \\ EB_{t,j,d_i},\ \forall\, j \in \Omega_2 \end{cases} \tag{10}$$

$$EB_{t,j,d_i} = G_{pv,t} - E_{req,t} + EB_{t-1,j,d_i} \tag{11}$$

$$G_{pv,t} = G_1.\,(1-\delta)^t \tag{12}$$

$$Eres_{d_i} = \sum_{t=0}^{nt} \frac{d_i}{(1+r)^t} \tag{13}$$

Eq. (5) represents the LCOE, which corresponds to the ratio between the net present value due an investment in a new electricity technology and the electricity delivered for this technology over its lifetime. As the prosumer is supplied in part by the PV system and in part by the distribution network, the net present value must take into account the investment and the maintenance costs of the PV system as well the respective payments for the DisCo (electricity bill). On the other hand, the electricity produced over the lifetime of this hybrid system (PV system and main distribution grid) corresponds to the total electricity demand over the period under analysis. Eq. (6) represents the net present value due the PV system investment while Eq. (7) represents the costs associated to this hybrid system, that is, the investment and the maintenance costs and the electricity bill to the DisCo due the network usage. Eq. (8) is used to calculate the electricity bill. Eq. (9) represents the fraction of the electricity bill that considers the monthly energy balance that corresponds to the accumulated value over the month of the energy taken from the network. Therefore, if the energy balance is less than the negative value of the equivalent demand of the cost of electricity availability, then the energy balance is used to compute the electricity bill, otherwise the equivalent demand of the cost of electricity availability is used.

Eq. (10) includes the taxes on the electricity bill. It should be noticed that the Federal Units that joined the Agreement 16 consider only the energy balance for this calculation while the remaining Federal Units consider the energy supplied from the network. Finally, Eq. (11) represents the energy balance throughout the months while Eq. (12) is the expected monthly electricity production of the PV system considering the efficiency loss δ as in (Mitscher and Rüther, 2012). Eq. (13) gives the total electricity delivered by the hybrid system over its lifetime which corresponds to the total electricity demand.

3.3. PV potential penetration

The threshold demand can be used to help potential investors in PV systems on their investment decisions. These investors are the residential consumers in a given DisCo area with a monthly electricity consumption larger than the threshold demand. As the EPE only makes public the information about the number of residential consumers according to their monthly consumption range for Brazilian regions and not by DisCo, the PV potential penetration was estimated using the average threshold demand by region and considering that the DisCos belonging to a same region have an equal number of residential consumers. Table 3 shows the EPE data that was used for these calculations (EPE, 2014).

3.4. Data and other assumptions

The daily profile for the residential electricity consumption used in this study was based on the data available in (PROCEL/COPPE, 2007) which was obtained through a survey focused on the identification of the electricity consumption habits for residential consumers. Despite the impact of the yearly temperature factor on the residential electricity consumption in Brazil (Ghisi et al., 2007), this study was carried out considering an average daily residential profile for all 63 DisCos (see Fig. 4). This approach is adequate to predict the threshold demand and the possible PV penetration for residential consumers in the Brazilian interconnected system. However, the individual behavior of the residential consumers in each DisCo, which is not publicly available, should be considered for studies addressing operation, expansion and quality of service in the distribution network.

Regarding the PV generation, we used a standard daily profile in

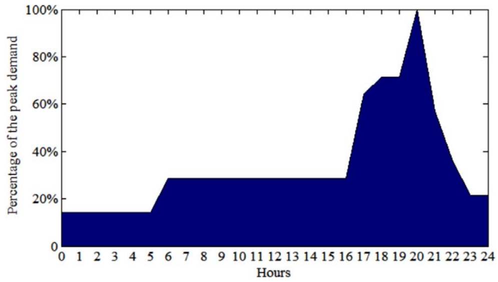

Fig. 4. Average daily profile for the residential consumers.

which power production starts at 6 a.m. and ends at 6 p.m. with a peak at 12 a.m. as shown in Fig. 5. It is important to notice that the PV generation is obtained using the approach described in Section 3.1 for a panel with horizontal inclination.

Regarding the total cost of the PV system, it consists of the cost of the modules, the installation cost, the inverter cost, the bidirectional meter cost, the cables cost, the protection and maintenance costs. In this study we considered the value of 2.31 USD/kWp[1] based on (Energy Research Company (EPE), 2012). This cost includes all mentioned components and the life cycle for the PV modules and the inverters are set at 25 and 12.5 years respectively. Table 4 details the PV data sheet used in this research.

This study considers the different energy tariffs in force in the DisCos in Brazil. Each of the 63 DisCo has its own tariff defined by ANEEL (2017b)). Besides, this paper considers the global horizontal irradiance in each Federal Units that corresponds to the DisCos concession area and the ICMS rate by consumption electricity range for each Federal Unit. Note that the monthly increase of the electricity tariff (β) was also considered as in (Lacchini and Rüther, 2015) based on the data published by ANEEL which indicates an increase of 2.3% per year for this rate. The connection between the residences and the main distribution grid is assumed to be three phase, which means that the equivalent demand of the cost of electricity availability (dcea) is 100 kWh. The maximum monthly residential demand (dmax) is set at 1000 kWh. Finally, the discount rate for the calculation of LCOE is 6% as in (Lacchini and Rüther, 2015). This rate corresponds closely to the average return of savings in Brazil and was very stable over the last years (Portal Brasil, 2017). Several studies use for this purpose the reference rate of the Special System of Clearance and Custody (SELIC) but is happens that this rate has a very unstable behavior to be considered over a long planning horizon.

4. Results

This section details the results obtained by applying the methodology described in the previous section. The iterative calculations were performed in order to estimate the threshold demand for each DisCo. Then, the average threshold demand by region was calculated and the number of potential investors as well as the potential PV penetration were obtained. In general, the LCOE associated to the PV systems is expected to decrease with the increase of the residential demand since they were sized aiming to supply the *applicable demand*. However, there are demand values for which there is a sharp increase in the LCOE. This observation is due to the extra investment requirements to cope with the increase in the demand, namely when an extra number of PV panels is required thus imposing a sharp increase of the investment costs. This type of situation can be observed in Fig. 6 and Fig. 7 in which we present the best and the worse LCOE behaviors respectively among all the 63 DisCos in the Brazilian interconnected system. The DisCo EMT located in the federal unit of Mato Grosso displays the best result with the grid parity being reached for 195 kWh. On the other hand, the DisCo AmE located in the federal unit of Amazonas presents the worse LCOE behavior, that is, the grid parity was far from being achieved.

Note that the residential demand values between 100 and 1000 kWh increased in steps of 1 kWh were used to size the PV systems. The local solar irradiation for all the local conditions of the DisCos and the energy balance for the PV system lifetime (25 years) have been considered to compute cash flows and the respective LCOE.

The grid parity was obtained for 49 of the 63 DisCos that exist in the interconnected Brazilian system. The values of the threshold demand are displayed in Fig. 8. According to these results, 14 of 63 DisCos do not have a threshold demand less than 1000 kWh, namely AmE, CEEE-D, Celesc-Dis, CFLO, Cocel, Cooperaliança, Copel-Dis, DMED, EFLIC, EFLUL, ELFSM, Escelsa, Forcel and Ienergia. Based on these results, it is interesting to notice that from these 14 DisCo that have no economic viability for PV systems for the considered monthly residential demand range (i.e. between 100 and 1000 kWh), 12 DisCos belong to the Federal Units that did not sign the Agreement 16. This result highlights the importance of the rules established in this agreement to ensure the economic viability for DG projects.

[1] The calculations were performed using the exchange rate between Brazilian Reais (BRL) and American Dolar (USD) of 1 BRL = 0.3025 USD.

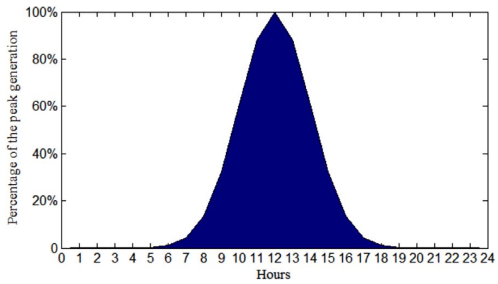

Fig. 5. PV generation profile used in this research.

Table 4
PV data sheet.

Technology	Polycrystalline
Nominal Power	240 Wp
Annual Power Decline	0.8%
Panel Area	1.65 m^2
Module Lifetime	25 years
Inverter Lifetime	12.5 years
Conversion efficiency	15%

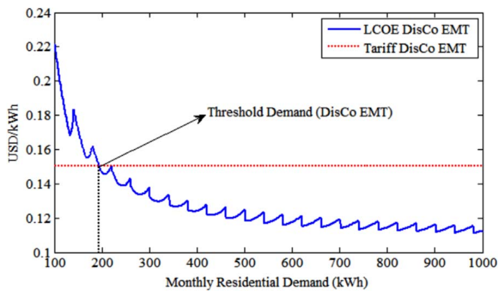

Fig. 6. Best LCOE result for the DisCos in the Brazilian Interconnected System – EMT Disco.

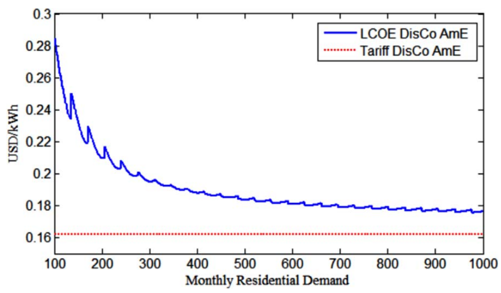

Fig. 7. Worst LCOE result for the DisCos in the Brazilian Interconnected System – AmE Disco.

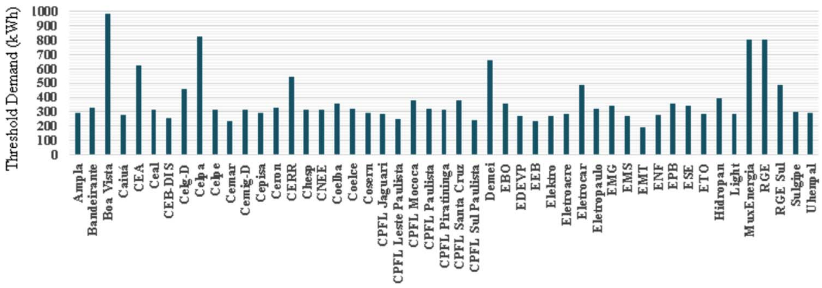

Fig. 8. The threshold demand for of each Brazilian DisCo.

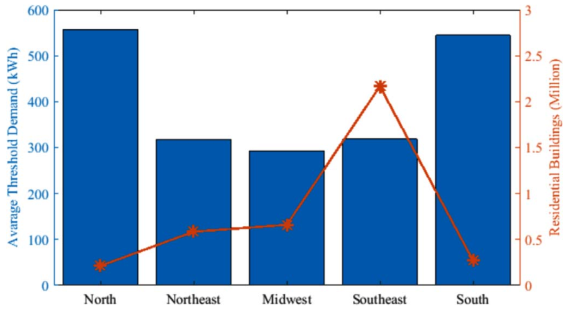

Fig. 9. Potential investors and the average threshold demand by region.

Table 5
PV system penetration.

Region	Penetration (MWp)
North	561.52
Northeast	421.05
Midwest	475.20
Southeast	1560.20
South	648.00

Bearing in mind the threshold demand for each DisCo, the average threshold demand by Brazilian region and the number of residential buildings with a monthly demand larger than this average demand, it is now possible to estimate the number of consumers that are potential investors in PV systems since it is guaranteed the grid parity in 25 years. This means that for these consumers the investment in the PV system is economically feasible, that is, the respective LCOE is below the current tariff. Fig. 9 presents the average threshold demand and the estimate of the number of potential investors, both by Brazilian region.

In order to estimate the PV system penetration by Brazilian region, the PV systems are sized to meet the applicable demand related to each regional average threshold demand, that is, the PV system must meet the difference between the regional average threshold demand and the equivalent demand of the cost of electricity availability (100 kWh). Therefore, the penetration of PV systems by Brazilian region of solar generation on the condition that the associated investments are economically viable can be estimated using the number of potential investors displayed in Fig. 9. According to this approach, the total PV penetration in the interconnected Brazilian system associated to economically viable investments is about 3666 MWp corresponding to almost 4 million residences becoming prosumers. Table 5 discriminates the values of the installed capacity by region.

5. Conclusion and policy implications

The introduction of government legislation and incentives in Brazil for Distributed Generation (DG) is increasing the participation of renewable sources in the Brazilian mix over the last few years, especially regarding Photovoltaic (PV) systems. After the deployment of the Net Metering regulation scheme in 2012, almost 25 MWp of PV systems were installed in residential buildings in Brazil, more than 92% of them after the publication of the Agreement 16, in 2015. Nevertheless, no one work in the literature reports results exploring the penetration of PV systems taking into account all the policies and regulatory issues as the Agreement 16 ant the Normative Resolutions 482 and 414.

The present work describes an additional contribution in this direction since it presents a technical-economic analysis and an approach to estimate the penetration of PV systems considering all the policy and regulatory issues in Brazil. First of all, the minimum demand to ensure the economic viability for PV systems – the *threshold demand* – has been computed for all distribution concession areas in Brazil considering the Levelized Cost of Energy (LCOE) associated to the investment in PV systems. Then, the potential penetration for this technology in all Brazilian regions was estimated considering that the residential buildings in each distribution company (DisCo) with a monthly residential demand greater than the threshold demand are potential investors in PV systems.

According to developed methodology, there are about 4 million residential buildings in Brazil that have technical-economic viability to invest in PV systems in the next 25 years, which corresponds to about 3666 MWp of electricity generation coming from this distributed generation technology. Bearing in mind that the current residential PV distributed generation in Brazil is about 25 MWp and that the Brazilian regulator ANEEL expects to have 2000 MWp of PV capacity installed in residential buildings in the next 10 years, new incentive policies still need to be implemented or improved to achieve this goal. The authors believe that financing mechanisms to facilitate the access to the capital required to invest in PV systems can be a good path since currently there are no instruments made available by the National Development Bank (BNDES) specifically directed to individual consumers that want to become prosumers. In addition, the results obtained strongly recommend the adhesion to the Agreement 16 for all Federal Units of Brazil since it is clear that in the Federal Units that did not followed this agreement the deployment of PV systems will be much more difficult.

Acknowledgements

This work was supported in part by the Coordination for the Improvement of Higher Education Personnel (CAPES, Brazil) under Grant 13207-13-0.

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